

**Lab3\_LejunChen**

In [1]:

```
%load_ext autoreload
%autoreload 2
```

In [2]:

```
import matplotlib
import matplotlib.pyplot as plt
import scipy.io
from mpl_toolkits.mplot3d import axes3d
from pdffuns import *
import sys
import getopt
import numpy as np
import scipy.io as io
import math
from pdffuns import norm2D, classplot
import pickle

pfile='lab3.p'
with open(pfile, "rb") as fp:
    X=pickle.load(fp)
```

In [3]:

```
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "last" # all / last / last_expr / none
```

In [4]:

```
X[0]=np.matrix(X[0])
X[1]=np.matrix(X[1])
X
```

Out[4]:

```
[matrix([[2.8, 2. , 2.8, 3. ],
         [4.8, 5.8, 6.9, 5.8]]),
 matrix([[ 1.7,  2.9,  3.8],
         [-2.6,  0.2, -2.9]])]
```

In [5]:

```
X[1][:,1].reshape(2,1).shape
```

Out[5]:

```
(2, 1)
```

In [6]:

```
#caculate the prior probabilites for each class
np.shape(X[0])
np.shape(X[1])
X[0].shape[1]
pw0=X[0].shape[1]/(X[0].shape[1]+X[1].shape[1])
pw0=round(pw0,3)
pw1=X[1].shape[1]/(X[0].shape[1]+X[1].shape[1])
pw1=round(pw1,3)
Pw = np.array([pw0, pw1])
print("The prior probabilites for each class are: ",Pw)
```

The prior probabilites for each class are: [0.571 0.429]

In [7]:

```
#check how many samples for each class in the datasets
N=[]
M=len(X)
for i in range(0, M):
    [l,p]=X[i].shape
    N.append(p)
print(l,N)
```

2 [4, 3]

a) mean for each class

$$\hat{\mu}_i = \frac{1}{N_i} \sum_{j=1}^N \mathbf{x}_j$$

In [8]:

```
mu=[None, None]
mu0=np.mean(X[0], axis=1)
mu1=X[1].mean(1)
mu[0]=mu0
mu[1]=mu1
print("The estimation of mean for class 1 is:\n",mu[0])
print("The estimation of mean for class 2 is:\n",mu[1])
```

The estimation of mean for class 1 is:

```
[[2.65 ]
 [5.825]]
```

The estimation of mean for class 2 is:

```
[[ 2.8      ]
 [-1.76666667]]
```

b) covariance matrix

$$\Sigma_i = \frac{1}{N_i} \sum_{j=1}^N (\mathbf{x}_j - \mu_i)(\mathbf{x}_j - \mu_i)^T$$

In [9]:

```
S = [None, None]
S[0] = X[0]-mu[0]
S[1] = X[1]-mu[1]
X[0]
```

Out[9]:

```
matrix([[2.8, 2. , 2.8, 3. ],
        [4.8, 5.8, 6.9, 5.8]])
```

In [10]:

```
Sgm=[None, None]
Sgm[0]=1/4*(S[0][:,0]*S[0][:,0].T+S[0][:,1]*S[0][:,1].T+S[0][:,2]*S[0][:,2].T+S[0][:,3]*S[0][:,3].T)
Sgm[0]
Sgm[1]=1/3*(S[1][:,0]*S[1][:,0].T+S[1][:,1]*S[1][:,1].T+S[1][:,2]*S[1][:,2].T)
Sgm[1]
print("The estimation of covariance matrix for class 1 is:\n",Sgm[0])
print("The estimation of covariance matrix for class 2 is:\n",Sgm[1])
```

The estimation of covariance matrix for class 1 is:

```
[[0.1475  0.00375 ]
 [0.00375 0.551875]]
```

The estimation of covariance matrix for class 2 is:

```
[[ 0.74      -0.00666667]
 [-0.00666667 1.94888889]]
```

In [11]:

```
def cov(Y_wi,my):
    [d,num]=Y_wi.shape
    sum=np.zeros((d, d))
    for k in range(0,num):
        temp=Y_wi[:,k].reshape(d,1)-my
        sum=sum+np.dot(temp,temp.transpose())
    cov=sum/num
    return cov
cov(X[0],mu[0])
```

Out[11]:

```
matrix([[0.1475 , 0.00375 ],
        [0.00375 , 0.551875]])
```

In [12]:

```
#cov1=np.cov(X[1])
#cov0=np.cov(X[0])
```

c) Plot the discriminant function for class 1.

In [13]:

```

#Define 25 points of computation along each axis
#x1 = np.arange(-5, 10, 0.6)
#x1 = x1.reshape(x1.size, 1)
#x2 = np.arange(-5, 10, 0.6)
#x2 = x2.reshape(x2.size, 1)
#x1.size
#x2.size
inc = 0.25
x1 = np.arange(-5, 10 + inc, inc)
x1 = x1.reshape(x1.size, 1)
x2 = np.arange(-5, 10 + inc, inc)
x2 = x2.reshape(x2.size, 1)

```

In [14]:

```

M = len(mu)
px = 0
pxw = []
g = []

```

In [15]:

```

for i in range(0, M):
    pxw.append([])
    [pxw[i], X1, X2] = norm2D(mu[i], Sgm[i], x1, x2)
    g.append(Pw[i] * pxw[i]) #scaled class probability function
    px=px+Pw[i] * pxw[i]

```

In [16]:

```

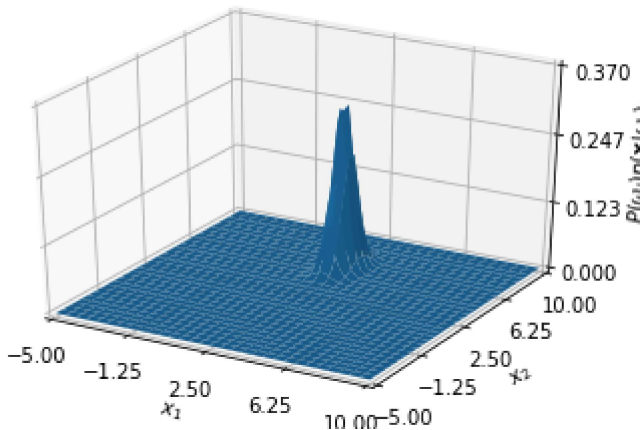
def posterior(g):
    posterior=[]
    M=len(g)
    px = sum(g)
    for i in range(0, M):
        posterior.append(np.divide(g[i], px))
    return posterior

```

In [17]:

```
print('Scaled')
gnan = 1
discr = 'Pwpwxw'
q = []
q.append(Pw[0] * pxw[0])
classplot(q, x1, x2, gnan, discr, 1)
```

Scaled



&lt;Figure size 432x288 with 0 Axes&gt;

d) Plot two discriminant function in the same plot.

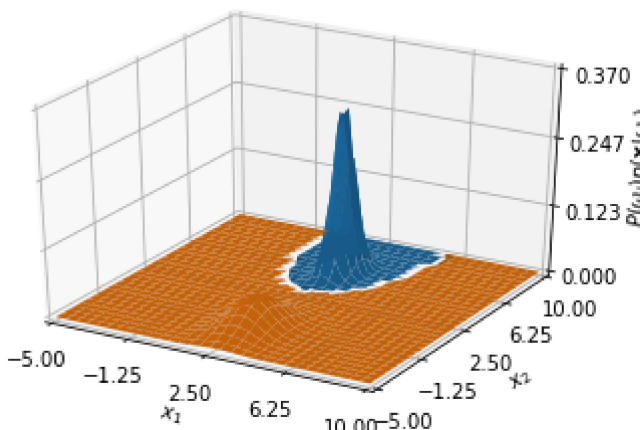
In [18]:

```
print('Scaled')
gnan = 1
discr = 'Pwpwxw'
classplot(g, x1, x2, gnan, discr, 1)
```

Scaled

C:\Users\junec\OneDrive\Documents\cs\courses\_term2\Machine Learning\assignment\_upload\exercise3\lab3\_sol\_lejun\pdfuns.py:64: UserWarning: Z contains NaN values. This may result in rendering artifacts.

```
obj = ax.plot_surface(X1, X2, G, facecolor=col[i])
```



&lt;Figure size 432x288 with 0 Axes&gt;

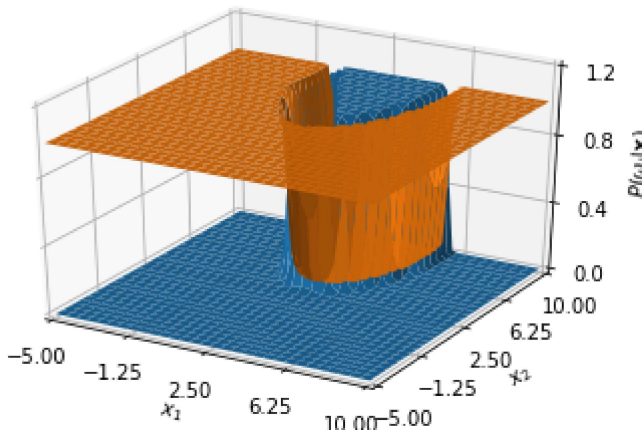
### The corresponding posterior probability function plotting

$$p(x | \omega_1) = (p(\omega_1)p(\omega_1 | x)) / (p(\omega_1)p(\omega_1 | x) + p(\omega_2)p(\omega_2 | x))$$

In [19]:

```
print('Posterior')
discr='Pwx'
gnan=0
classplot(posterior(g), x1, x2, gnan, discr, 1)
```

Posterior



&lt;Figure size 432x288 with 0 Axes&gt;

e) The decision border is shown in the above plot.

f) Repeat subtask c-d for the Parzen classifier with window size  $h_1 = 0.5$ .

In [20]:

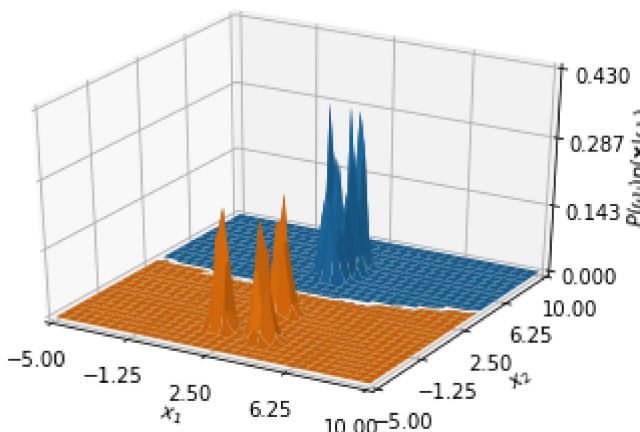
```
def ParW(h1):
    g = []
    pxw=[]
    for k in range(0,M):
        hn=h1/np.sqrt(N[k])
        hnI=hn**2*np.identity(1)
        pxw.append([])
        pxw[k]=0
        for i in range(0,N[k]):
            xk=X[k][:,i].reshape(1,1)
            [pn,X1,X2]=norm2D(xk,hnI,x1,x2)
            print("norm2D value",pn[0])
            print("norm2D value len",len(pn[0]))
            pxw[k]=pxw[k]+pn
        pxw[k]=pxw[k]/N[k]
        g.append(Pw[k] * pxw[k])
    return g
```



```

6.02066977e-096 3.78308148e-100 1.12286028e-104 1.57429054e-109
1.04261313e-114 3.26167459e-120 4.81989094e-126 3.36444110e-132
1.10934796e-138 1.72783308e-145 1.27120303e-152 4.41781161e-160
7.25234748e-168 5.62379077e-176 2.05996027e-184 3.56424600e-193
2.91310164e-202]
norm2D value len 61
norm2D value [9.97657140e-214 2.00214352e-202 1.89796516e-191 8.49885472e-
181
1.79767721e-170 1.79614816e-160 8.47718660e-151 1.88990714e-141
1.99025318e-132 9.90045895e-124 2.32638434e-115 2.58218137e-107
1.35385190e-099 3.35300896e-092 3.92263055e-085 2.16770030e-078
5.65848551e-072 6.97718626e-066 4.06386773e-060 1.11809306e-054
1.45309991e-049 8.92056039e-045 2.58683030e-040 3.54342202e-036
2.29275135e-032 7.00761406e-029 1.01172511e-025 6.89976065e-023
2.22271949e-020 3.38231795e-018 2.43121485e-016 8.25489187e-015
1.32397132e-013 1.00305536e-012 3.58963562e-012 6.06813130e-012
4.84550126e-012 1.82768602e-012 3.25644397e-013 2.74072062e-014
1.08959490e-015 2.04618312e-017 1.81511051e-019 7.60572786e-022
1.50541983e-024 1.40751691e-027 6.21625395e-031 1.29682990e-034
1.27795752e-038 5.94879443e-043 1.30803885e-047 1.35859954e-052
6.66563336e-058 1.54479381e-063 1.69113686e-069 8.74512717e-076
2.13615441e-082 2.46478075e-089 1.34339301e-096 3.45865317e-104
4.20620156e-112]
norm2D value len 61

```



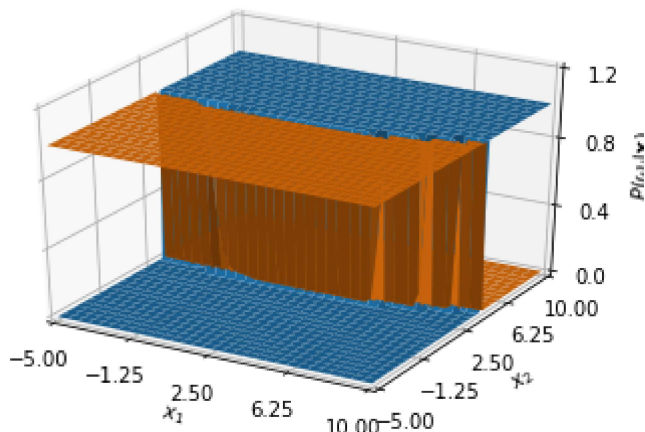
<Figure size 432x288 with 0 Axes>



In [22]:

```
print('Posterior')
discr='Pwx'
gnan=0
classplot(posterior(g), x1, x2, gnan, discr, 1)
```

Posterior



&lt;Figure size 432x288 with 0 Axes&gt;

**g)** Repeat subtask c-d for the Parzen classifier with window size  $h_1 = 5$

In [23]:

```

h1=5
print('Scaled')
gnan = 1
discr = 'Pwpwx'
g=ParW(h1)
classplot(g, x1, x2, gnan, discr, 1)
7.96177550e-06 7.25471809e-06 6.54467687e-06 5.84538247e-06
5.16885931e-06 4.52515589e-06 3.92219728e-06 3.36575406e-06
2.85951499e-06 2.40524562e-06 2.00301196e-06 1.65144726e-06
1.34804046e-06 1.08942717e-06 8.71666858e-07 6.90494016e-07
5.41534787e-07 4.20484369e-07 3.23243952e-07 2.46018640e-07
1.85379914e-07]
norm2D value len 61
norm2D value [4.47730908e-08 5.89451474e-08 7.68309310e-08 9.91473678e-08
1.26672790e-07 1.60229523e-07 2.00659072e-07 2.48789537e-07
3.05395393e-07 3.71150376e-07 4.46574977e-07 5.31980751e-07
6.27414437e-07 7.32605463e-07 8.46920904e-07 9.69332128e-07
1.09839720e-06 1.23226264e-06 1.36868719e-06 1.50508899e-06
1.63861607e-06 1.76623829e-06 1.88485714e-06 1.99142812e-06
2.08308929e-06 2.15728832e-06 2.21190034e-06 2.24532893e-06
2.25658369e-06 2.24532893e-06 2.21190034e-06 2.15728832e-06
2.08308929e-06 1.99142812e-06 1.88485714e-06 1.76623829e-06
1.63861607e-06 1.50508899e-06 1.36868719e-06 1.23226264e-06
1.09839720e-06 9.69332128e-07 8.46920904e-07 7.32605463e-07
6.27414437e-07 5.31980751e-07 4.46574977e-07 3.71150376e-07
3.05395393e-07 2.48789537e-07 2.00659072e-07 1.60229523e-07

```

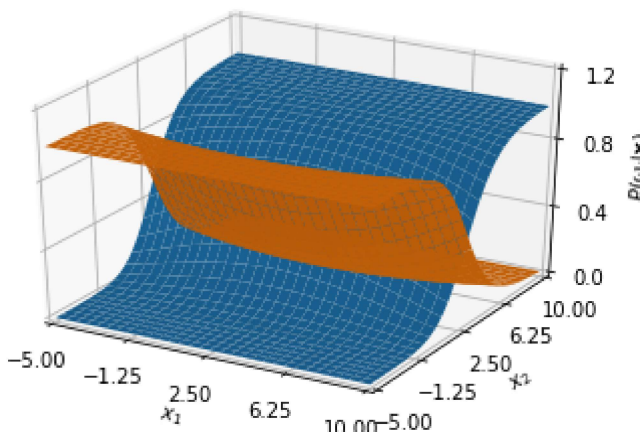
In [24]:

```

print('Posterior')
discr='Pwx'
gnan=0
classplot(posterior(g), x1, x2, gnan, discr, 1)

```

Posterior



&lt;Figure size 432x288 with 0 Axes&gt;

h) Repeat the previous subtask the kN-nearest neighbour classifier with kn = 1.

In [25]:

```
def NearNeib(kn,x1,x2):
    a_list=[]
    g=[]
    X1,X2 = np.meshgrid(x1,x2)
    [m,n]=np.shape(X1)
    f=0
    for k in range(0,M):
        p = np.zeros(np.shape(X1))
        for i in np.arange(0, m):
            for j in np.arange(0, n):
                a=np.array([[X1[i,j]], [X2[i,j]]])
                a_list.append(a)
                dist=[]
                for q in range(0,N[k]):
                    b=X[k][:,q]
                    d = np.linalg.norm(a-b)
                    dist.append(d)

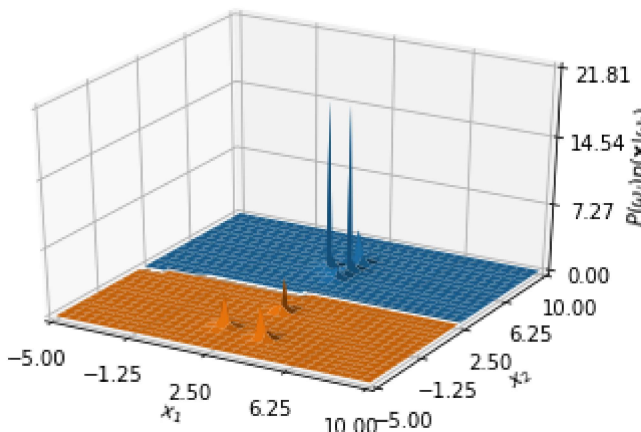
                dist_sort=sorted(dist)
                p[i,j]=Pw[k]*kn/N[k]/(math.pi*dist_sort[kn-1]**2)

    g.append(p)
    return g
```

In [26]:

```
print('Scaled')
gnan = 1
discr = 'Pwpw'
g=NearNeib(1,x1,x2)
classplot(g, x1, x2, gnan, discr, 1)
```

Scaled



&lt;Figure size 432x288 with 0 Axes&gt;

In [27]:

g

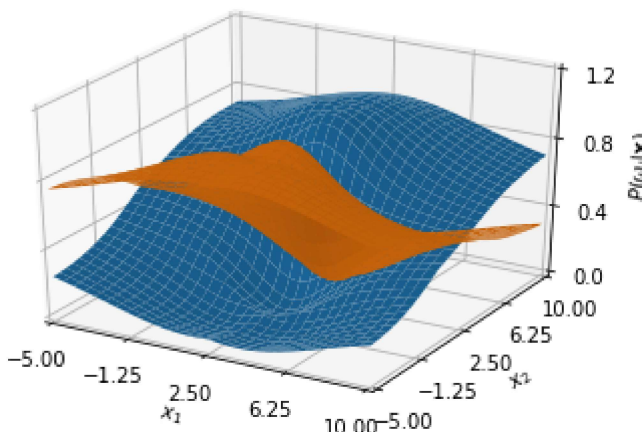
Out[27]:

```
[array([[0.00028964, 0.0002969 , 0.00030428, ..., 0.00032242, 0.0003148 ,
        0.00030727],
       [0.00029886, 0.00030659, 0.00031447, ..., 0.00033388, 0.00032571,
        0.00031766],
       [0.00030841, 0.00031666, 0.00032507, ..., 0.00034586, 0.0003371 ,
        0.00032848],
       ...,
       [0.00072482, 0.00076687, 0.00081228, ..., 0.00087974, 0.00082522,
        0.00077541],
       [0.00070336, 0.00074289, 0.00078542, ..., 0.00085713, 0.00080529,
        0.00075779],
       [0.00068185, 0.00071894, 0.0007587 , ..., 0.00083374, 0.00078461,
        0.00073944]]),
 array([[0.00089868, 0.00096106, 0.00102983, ..., 0.00123356, 0.00114332,
        0.00106227],
       [0.00091933, 0.00098471, 0.00105703, ..., 0.00126748, 0.0011724 ,
        0.00108733],
       [0.00093852, 0.00100676, 0.00108248, ..., 0.00129867, 0.00119903,
        0.00111102 ],
       ...,
       [0.0003057 , 0.00031389, 0.00032225, ..., 0.00035001, 0.00034118,
        0.00033249],
       [0.00029632, 0.00030401, 0.00031185, ..., 0.00033777, 0.00032954,
        0.00032143],
       [0.00028727, 0.0002945 , 0.00030185, ..., 0.00032606, 0.00031839,
        0.00031081]])]
```

In [28]:

```
print('Posterior')
discr='Pwx'
gnan=0
classplot(posterior(g), x1, x2, gnan, discr, 1)
```

Posterior



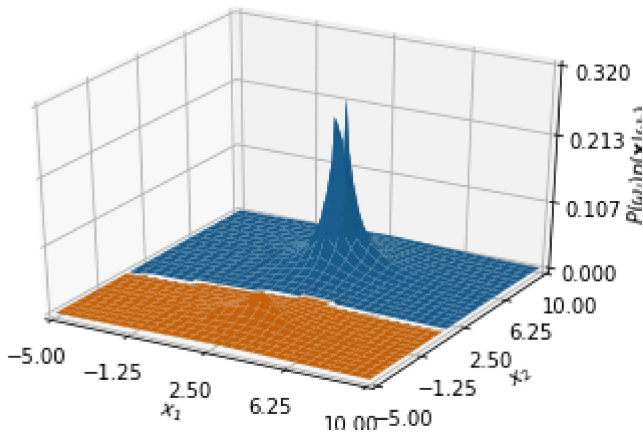
&lt;Figure size 432x288 with 0 Axes&gt;

i) Repeat the previous subtask the kN-nearest neighbour classifier with kn = 3.

In [29]:

```
print('Scaled')
gnan = 1
discr = 'Pwpwx'
g=NearNeib(3,x1,x2)
classplot(g, x1, x2, gnan, discr, 1)
```

Scaled

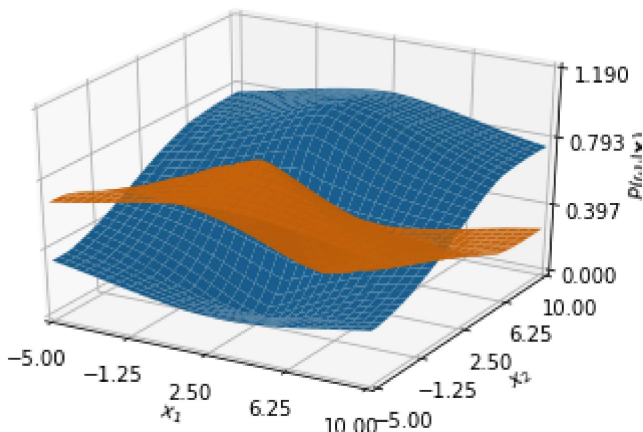


&lt;Figure size 432x288 with 0 Axes&gt;

In [30]:

```
print('Posterior')
discr='Pwx'
gnan=0
classplot(posterior(g), x1, x2, gnan, discr, 1)
```

Posterior



&lt;Figure size 432x288 with 0 Axes&gt;

j) Repeat the previous subtask the kN-nearest neighbour classifier with  $kn = 5$ . (Why will this not work?)

In [ ]:

*Search for the fifth nearest neighbour, but there are just 4 neighbours for class 1, and 3 neighbours for class 2.*

**k)** Add functionality so that the figure display the a posteriori probability for the two classes: *See the corresponding parts above.*