#### Important Note for question4!

- Please do not change the default variable names in this problem, as we will use them in different parts.
- The default variables are initially set to "None".
- You only need to modify code in the "TODO" part. We added a lot of "assertions" to check your code. **Do not** modify them.

```
# load packages
import numpy as np
import pandas as pd
import time
from sklearn.naive_bayes import GaussianNB
```

## P1. Load data and plot

#### **TODO**

Load train and test data, and split them into inputs(trainX, testX) and labels(trainY, testY)

## P2. Write your Gaussian NB solver

#### **TODO**

- Finish the myNBSolver() function.
  - Compute P(y == 0) and P(y == 1), saved in "py0" and "py1"
  - Compute mean/variance of trainX for both y = 0 and y = 1, saved in "mean0", "var0", "mean1" and "var1"
    - Each of them should have shape (N*train, M*), where Ntrain is number of train samples and M is number of features.
  - Compute P(xi I y == 0) and P(xi I y == 1), compare and save binary prediction in "trainpred" and "testpred"
  - Compute train accuracy and test accuracy, saved in "trainacc" and "testacc".
  - Return train accuracy and test accuracy.

```
def myNBSolver(trainX, trainY, testX, testY):
   N train = trainX.shape[0]
   N_test = testX.shape[0]
   M = trainX.shape[1]
   #### TODO ####
   # Compute P(y == 0) and P(y == 1)
   y0 = np.argwhere(trainY == 0)
   y1 = np.argwhere(trainY == 1)
   x0 = trainX[y0]
   x1 = trainX[y1]
   x0 = x0.squeeze()
    x1 = x1.squeeze()
   py0 = len(y0)/N_train
   py1 = len(y1)/N_train
    ###############
    print("Total probablity is %.2f. Should be equal to 1." %(py0 + py1))
    #### TODO ####
   # Compute mean/var for each label
   mean0 = np.mean(x0,axis=0)
    # print(mean0.shape)
```

```
mean1 = np.mean(x1,axis=0)
var0 = np.mean((x0-mean0)**2,axis=0)
var1 = np.mean((x1-mean1)**2,axis=0)
################
assert(mean0.shape[0] == M)
#### TODO ####
# Compute P(xi|y == 0) and P(xi|y == 1), compare and make prediction
# This part may spend 5 - 10 minutes or even more if you use for loop,
# print something (like step number) to check the progress
p \times y0 = (2*np.pi*var0)**(-0.5)*np.exp(-((trainX-mean0)**2)/(2*var0))
p_xy1 = (2*np.pi*var1)**(-0.5)*np.exp(-((trainX-mean1)**2)/(2*var1))
prod0 = py0* np.prod(p_x_y0,axis=1)
prod1 = py1* np.prod(p_x_y1,axis=1)
train ans = np.ones(N train)
pos0 = np.argwhere(prod0>prod1)
train ans[pos0] = 0
p \times y_0 \text{ test} = (2*np.pi*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*np.exp(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-0.5)*(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/(2*var0)**(-((testX-mean0)**2)/
p_x_y1_{\text{test}} = (2*np.pi*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*np.exp(-((testX-mean1)**2)/(2*var1)**(-0.5)*(-(testX-mean1)**(-0.5)*(-(testX-mean1)**2)/(2*var1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)**(-(testX-mean1)*
prod0_test = py0* np.prod(p_x_y0_test,axis=1)
prod1_test = py1* np.prod(p_x_y1_test,axis=1)
test ans = np.ones(N test)
pos0_test = np.argwhere(prod0_test>prod1_test)
test_ans[pos0_test] = 0
train pred = train ans
test_pred = test_ans
##############
assert(train pred[0] == 0 or train pred[0] == 1)
assert(test_pred[0] == 0 or test_pred[0] == 1)
#### TODO ####
# Compute train accuracy and test accuracy
train_acc = len(np.argwhere(train_pred==trainY))/N_train
test_acc = len(np.argwhere(test_pred==testY))/N_test
########()
return train_acc, test_acc
```

```
# driver to test your NB solver
train_acc, test_acc = myNBSolver(trainX, trainY, testX, testY)
print("Train accuracy is %.2f" %(train_acc * 100))
print("Test accuracy is %.2f" %(test_acc * 100))
```

```
Total probablity is 1.00. Should be equal to 1.
Train accuracy is 92.22
Test accuracy is 92.05
```

## P3. Test your result using sklearn

#### **TODO**

- Finish the skNBSolver() function.
  - fit model, make prediction and return accuracy for train and test sets.

```
# driver to test skNBSolver
sk_train_acc, sk_test_acc = skNBSolver(trainX, trainY, testX, testY)
print("Train accuracy is %.2f" %(sk_train_acc * 100))
print("Test accuracy is %.2f" %(sk_test_acc * 100))
```

```
Train accuracy is 92.22
Test accuracy is 92.05
```

```
# from google.colab import drive
# drive.mount('/content/drive')
```

```
# %cd /content/drive/MyDrive/24787/hw3/data_and_code
```

```
[WinError 3] The system cannot find the path specified: '/content/drive/M yDrive/24787/hw3/data_and_code' e:\drive\24787\hw3\data_and_code
```

#### Note for question1

- Please follow the template to complete q1
- You may create new cells to report your results and observations

```
# Import libraries
# load packages
import numpy as np
import pandas as pd
import time
from sklearn.naive_bayes import GaussianNB
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
```

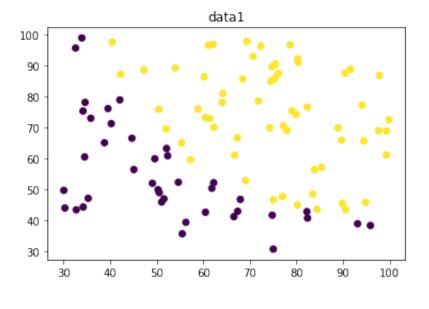
# A. Load data and plot

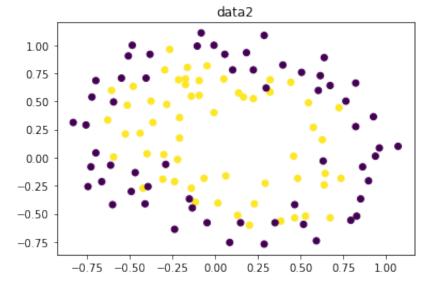
#### **TODO**

- · load data
- plot the points of different labels with different color

## Q2 (a)

```
# Load dataset
data1 = np.loadtxt("ex2data1.txt",delimiter=',')
data2 = np.loadtxt("ex2data2.txt",delimiter=',')
def readdata(filename):
    data = np.loadtxt(filename,delimiter=',')
    X = data[:,:-1]
    Y = data[:,-1].reshape(-1,1)
    return X,Y
def plotscatter(X,Y,title=None):
    plt.scatter(X[:,0],X[:,1],c=Y)
    plt.title(title)
    plt.show()
    # return fig
X1,Y1 = readdata("ex2data1.txt")
X2,Y2 = readdata("ex2data2.txt")
plotscatter(X1,Y1,title="data1")
plotscatter(X2,Y2,title="data2")
# print(Y1.shape)
# X1 = data1[:,:-1]
# Y1 = data1[:,-1]
\# X2 = data2[:,:-1]
# Y2 = data2[:,-1]
# print(X1.shape)
# fig =plt.figure()
# plt.scatter(X1[:,0],X1[:,1],c=Y1)
# fig =plt.figure()
# plt.scatter(X2[:,0],X2[:,1],c=Y2)
# Y1_reshape = Y1.reshape(-1,1)
# Plot points
```





# **B.** sigmoid function

## **TODO**

• name the sigmoid function sigmoid()

# Q2 (b)

```
#Define sigmoid function

def sigmoid(mat):
    return (1+np.exp(-mat))**(-1)
```

# C. loss function, gradient function

#### **TODO**

- Define loss function and name it loss()
- Define Gradient Function and name it gradient()

## Q2 (c)

```
#Define loss function
def loss(X,w,Y,e):
    return np.mean(-Y*np.log(sigmoid(X @ w)+e)-(1-Y)*np.log(1-sigmoid(X @ w)
#Define gradient function
def gradient(X,w,Y):
    return np.mean((sigmoid(X @ w)-Y)*X,axis= 0).reshape(-1,1)
```

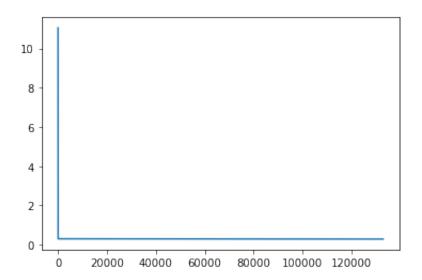
# D. prediction function, gradient descent and plot meshgrids

#### **TODO**

- Define a prediction function and name it predict()
- Using all above functions implement gradient descent with appropriate initialization, learning rates & # of initialization
- Use contourf/meshgrids or any other command to visualize the boundary conditions

## Q2 (d)

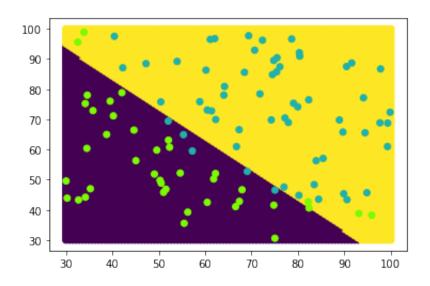
```
#Define prediction function
def predict(w,X):
    # print(f"{w.shape} {X.shape}")
    vector = X@w
    p = sigmoid(vector)
    pred = np.empty(vector.shape)
    pred[p>0.5] = 1
    pred[p <= 0.5] = 0
    return np.hstack((p, pred))
def plotloss(losslst):
    plt.plot(np.arange(len(losslst)), losslst)
    plt.show()
def train(X,Y,step=0.1,iter=1e6,threshold=1e-8,e=1e-8):
    new_X = np.ones((X.shape[0],X.shape[1]+1))
    new_X[:,1:] = X
    error = 1e5
    count = 0
    prev = 0
    J_lst = []
    w = np.array([[-65],[0],[0]],dtype=float)
    while error > threshold and count<iter:</pre>
        J = loss(new_X, w, Y1, e)
        G = gradient(new_X,w,Y1)
        w -= step*G
        error = np.abs(J-prev)
        prev = J
        J_lst.append(J)
        count+=1
    plotloss(J_lst)
    return w
w = train(X1,Y1,step=0.01,iter=1e6,threshold=1e-8,e=1e-8)
```



## Q2 (d)

```
def drawmesh(xrange,yrange,w,X,Y):
    xx = np.linspace(xrange[0], xrange[1], 100)
    yy = np.linspace(yrange[0], yrange[1], 100)
    xv, yv = np.meshgrid(xx, yy)
   xr= xv.ravel()
   yr = yv.ravel()
   new_X = np.ones((len(xr),3))
   new_X[:,1] = xr
   new_X[:,2] = yr
    soft = predict(w,new_X)
    # ListedColormap(["darkorange", "gold", "lawngreen", "lightseagreen"])
    print(f"predict results:\n {soft}")
    plt.scatter(xr,yr,c=soft[:,1])
   plt.scatter(X[:,0],X[:,1],c=Y,cmap=ListedColormap([ "lawngreen", "light
    plt.show()
drawmesh([30,100],[30,100],w,X1,Y1)
```

```
predict results:
  [[2.73278232e-14 0.00000000e+00]
  [3.86740529e-14 0.00000000e+00]
  [5.47311199e-14 0.00000000e+00]
  ...
  [1.00000000e+00 1.00000000e+00]
  [1.00000000e+00 1.00000000e+00]
  [1.00000000e+00 1.00000000e+00]]
```



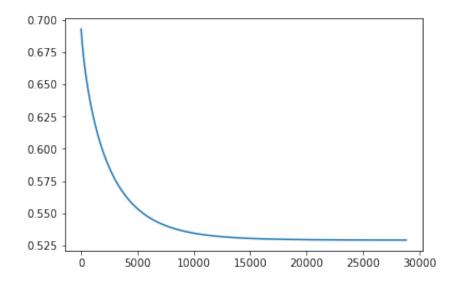
# E. Feature mapping, regularized Cost function, gradient function and gradient descent

#### **TODO**

- implement function **map\_feature()** to transform data from original space to the 28D space specified in the write-up
- Create a regularized loss function & gradient function and name it loss\_reg() and gradient\_reg()
- Using both these functions implement gradient descent with appropriate initialization, learning rates & # of initialization
- Use contourf/meshgrids or any other command to visualize the boundary conditions

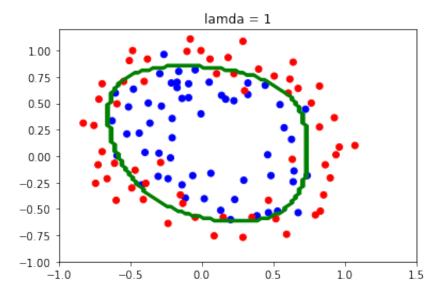
## Q3 (a)

```
feature lst= np.hstack((feature_lst,(x1**(k))*(x2**(j-k))))
      count +=1
  return feature_lst
def loss reg(X,Y,w,lamda, n,e):
    # just for the last part w, it will not take the bias term
    w_partial = w.copy()
    w partial[0,0] = 0
    return (np.mean(-Y*np.log(sigmoid(X @ w)+e)-(1-Y)*np.log(1-sigmoid(X @
def gradient reg(X, Y, w,lamda,n,e):
    w_partial = w.copy()
    w_partial[0,0] = 0
    g = np.mean((sigmoid(X @ w)-Y)*X, axis= 0).reshape((-1,1))+lamda * w pa
    return g
def train reg(X,Y,step=0.1,iter=1e6,threshold=1e-8,e=1e-8,lamda=1,loss pl
ot=True):
      new_X = map_feature_reg(X,6)
      error = 1e5
      count = 0
      prev = 0
      J lst = []
      w = np.zeros((28,1))
      n = new_X.shape[0]
      # print(n)
      while error > threshold and count<iter:
        J = loss reg(new X,Y,w,lamda,n,e)
        G = gradient_reg(new_X,Y,w,lamda,n,e)
        w -= step*G
        error = np.abs(J-prev)
        prev = J
        J_lst.append(J)
        count+=1
      if loss plot:
        plotloss(J lst)
      return w
w = train reg(X2, Y2, step=0.01, iter=1e6, threshold=1e-8, e=1e-8, lamda=1)
```



Here I define some functions to draw the boundry in both my method and sklearn.

```
def drawmesh_reg(xrange,yrange,w,X,Y,title=None,subplot=None):
   xx = np.linspace(xrange[0], xrange[1], 100)
    yy = np.linspace(yrange[0], yrange[1], 100)
   xv, yv = np.meshgrid(xx, yy)
   xr= xv.ravel()
   yr = yv.ravel()
   xc = xr.reshape(-1,1)
   yc = yr.reshape(-1,1)
    fake_x = np.hstack((xc,yc))
   new_X = map_feature_reg(fake_x)
   # print(new_X.shape)
   soft = predict(w,new X)
    # ListedColormap(["darkorange", "gold", "lawngreen", "lightseagreen"])
    if subplot==None:
        plt.contour(xv,yv,soft[:,1].reshape((-1,100)),colors ='green')
        # plt.scatter(xr,yr,c=soft[:,1])
        plt.scatter(X[:,0],X[:,1],c=Y,cmap=ListedColormap([ "red", "blue"])
        plt.title(title)
       plt.show()
    else:
        subplot.contour(xv,yv,soft[:,1].reshape((-1,100)),colors ='green')
        # subplot.scatter(xr,yr,c=soft[:,1])
        subplot.scatter(X[:,0],X[:,1],c=Y,cmap=ListedColormap([ "red", "blu
        subplot.set_title(title)
# fig, axs = plt.subplots(1,2,figsize=(16,8))
drawmesh_reg([-1,1.5],[-1,1.2],w,X2,Y2,title="lamda = 1",subplot=None)
```

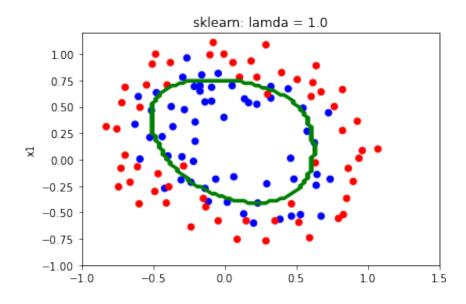


```
from sklearn import linear_model
def sk_mesh(xrange,yrange,X,Y,c=1,title=None,subplot=None):
    xx = np.linspace(xrange[0], xrange[1], 100)
    yy = np.linspace(yrange[0], yrange[1], 100)
    xv, yv = np.meshgrid(xx, yy)
    # print(xv.shape)
    xr= xv.ravel()
    yr = yv.ravel()
    xc = xr.reshape(-1,1)
    yc = yr.reshape(-1,1)
    fake_x = np.hstack((xc,yc))
    fake_X = map_feature_reg(fake_x)
    new_X = map_feature_reg(X)
    # print(f"{new_X.shape} {Y2.shape}")
    clf = linear_model.LogisticRegression(penalty="12", solver="liblinear",
    clf.set params(C=c)
    clf.fit(new X,Y2)
    w = clf.coef_.reshape(-1,1)
    soft = predict(w,fake_X)
    # print(soft.shape)
    # ListedColormap(["darkorange", "gold", "lawngreen", "lightseagreen"])
```

```
if subplot==None:
    plt.contour(xv,yv,soft[:,1].reshape((-1,100)),colors ='green')
    # plt.scatter(xr,yr,c=soft[:,1])
    plt.scatter(X[:,0],X[:,1],c=Y,cmap=ListedColormap([ "red", "blue"])
    plt.title(f"sklearn: lamda = {c**(-1)}")
    plt.ylabel("x2")
    plt.ylabel("x1")
    plt.show()

else:
    subplot.contour(xv,yv,soft[:,1].reshape((-1,100)),colors ='green')
    # subplot.scatter(xr,yr,c=soft[:,1])
    subplot.scatter(X[:,0],X[:,1],c=Y,cmap=ListedColormap([ "red", "blusubplot.set_title(f"sklearn: lamda = {c**(-1)}")
    # subplot.set_y
```

D:\anaconda\envs\piptorch\lib\site-packages\sklearn\utils\validation.py:9
93: DataConversionWarning: A column-vector y was passed when a 1d array w
as expected. Please change the shape of y to (n\_samples, ), for example u
sing ravel().
 y = column\_or\_1d(y, warn=True)



## F. Tune the strength of regularization

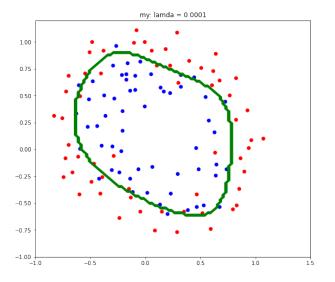
- tweak the hyper-parameter \$\lambda\$ to be \$[0, 1, 100]\$
- draw the decision boundaries

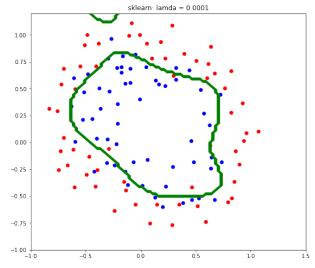
Here are the graphs for use my method and sklearn to draw the boundry in condition lamda = [0.0001,1,1000]

```
for i in [0.0001,1,100]:
    fig, axs = plt.subplots(1,2,figsize=(20,8))

w = train_reg(X2,Y2,step=0.01,iter=1e6,threshold=1e-8,e=1e-8,lamda=i,lo
    drawmesh_reg([-1,1.5],[-1,1.2],w,X2,Y2,title=f"my: lamda = {i}",subplot
    sk_mesh([-1,1.5],[-1,1.2],X2,Y2,c=i**(-1),subplot=axs[1])
    plt.show()
```

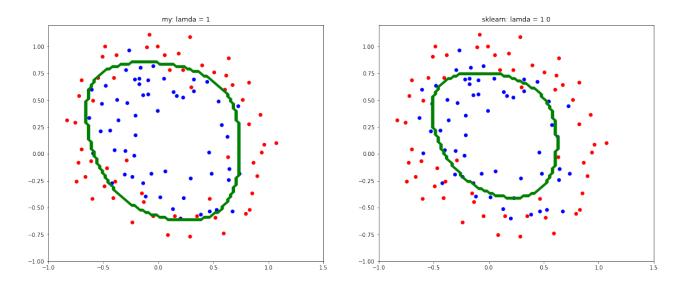
D:\anaconda\envs\piptorch\lib\site-packages\sklearn\utils\validation.py:9
93: DataConversionWarning: A column-vector y was passed when a 1d array w
as expected. Please change the shape of y to (n\_samples, ), for example u
sing ravel().
 y = column\_or\_1d(y, warn=True)
C:\Users\joeww\AppData\Local\Temp/ipykernel\_36808/570009302.py:4: Runtime
Warning: overflow encountered in exp
 return (1+np.exp(-mat))\*\*(-1)





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