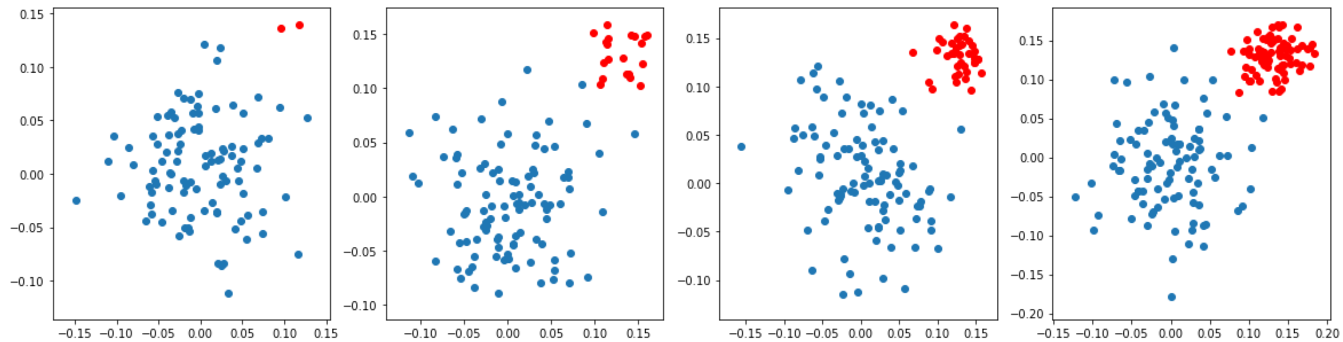
In [12]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import SGDClassifier
from sklearn.linear_model import LogisticRegression
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, Normalizer
import matplotlib.pyplot as plt
from sklearn.svm import SVC
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

In [13]:
```
def draw_line(coef,intercept, mi, ma):
    # for the separating hyper plane ax+by+c=0, the weights are [a, b] and the
 intercept is c
    # to draw the hyper plane we are creating two points
    # 1. ((b*min-c)/a, min) i.e ax+by+c=0 ==> ax = (-by-c) ==> x = (-by-c)/a he
re in place of y we are keeping the minimum value of y
    # 2. ((b*max-c)/a, max) i.e ax+by+c=0 ==> ax = (-by-c) ==> x = (-by-c)/a he
re in place of y we are keeping the maximum value of y
    points=np.array([[((-coef[1]*mi - intercept)/coef[0]), mi],[((-coef[1]*ma -
intercept)/coef[0]), ma]])
    plt.plot(points[:,0], points[:,1])
```

What if Data is imabalanced

1. As a part of this task you will observe how linear models work in case of data imbalanced
2. observe how hyper plane is changs according to change in your learning rate.
3. below we have created 4 random datasets which are linearly separable and having class imbalance
4. in the first dataset the ratio between positive and negative is 100 : 2, in the 2nd data its 100:20,
in the 3rd data its 100:40 and in 4th one its 100:80

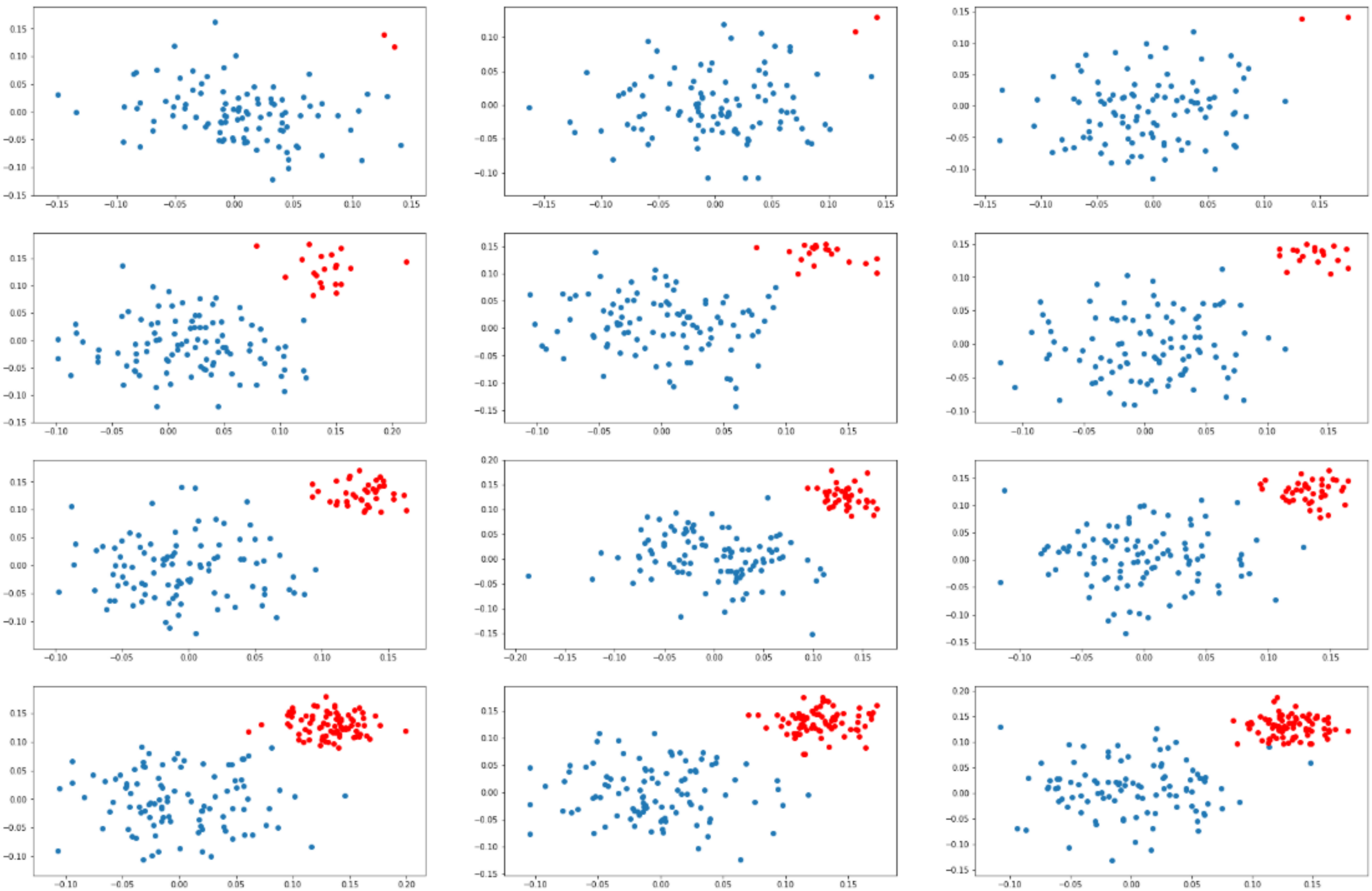
In [14]:
```
# here we are creating 2d imbalanced data points
ratios = [(100,2), (100, 20), (100, 40), (100, 80)]
plt.figure(figsize=(20,5))
for j,i in enumerate(ratios):
    plt.subplot(1, 4, j+1)
    X_p=np.random.normal(0,0.05,size=(i[0],2))
    X_n=np.random.normal(0.13,0.02,size=(i[1],2))
    y_p=np.array([1]*i[0]).reshape(-1,1)
    y_n=np.array([0]*i[1]).reshape(-1,1)
    X=np.vstack((X_p,X_n))
    y=np.vstack((y_p,y_n))
    plt.scatter(X_p[:,0],X_p[:,1])
    plt.scatter(X_n[:,0],X_n[:,1],color='red')
plt.show()
```



your task is to apply SVM (sklearn.svm.SVC (https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html#sklearn.svm.SVC)) and LR (sklearn.linear_model.LogisticRegression (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)) with different regularization strength [0.001, 1, 100]

Task 1: Applying SVM

1. you need to create a grid of plots like this



in each of the cell[i][j] you will be drawing the hyper plane that you get after applying SVM (https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html) on ith dataset and
jth learnig rate

i.e

Plane(SVM().fit(D1, C=0.001))	Plane(SVM().fit(D1, C=1))	Plane(SVM().fit(D1, C=100))
Plane(SVM().fit(D2, C=0.001))	Plane(SVM().fit(D2, C=1))	Plane(SVM().fit(D2, C=100))
Plane(SVM().fit(D3, C=0.001))	Plane(SVM().fit(D3, C=1))	Plane(SVM().fit(D3, C=100))
Plane(SVM().fit(D4, C=0.001))	Plane(SVM().fit(D4, C=1))	Plane(SVM().fit(D4, C=100))

if you can do, you can represent the support vectors in different colors,
which will help us understand the position of hyper plane

Write in your own words, the observations from the above plots, and what do you think about the position of the hyper plane

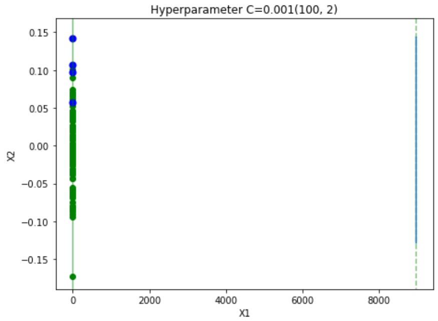
check the optimization problem here https://scikit-learn.org/stable/modules/svm.html#mathematical-formulation

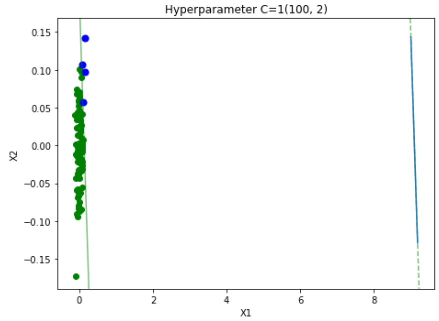
if you can describe your understanding by writing it on a paper
and attach the picture, or record a video upload it in assignment.

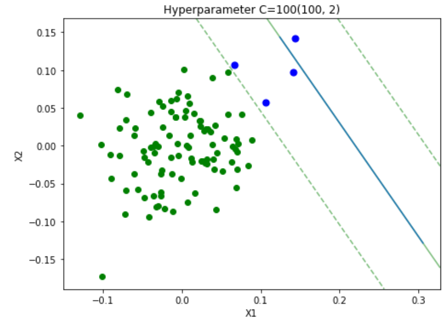
In [34]:

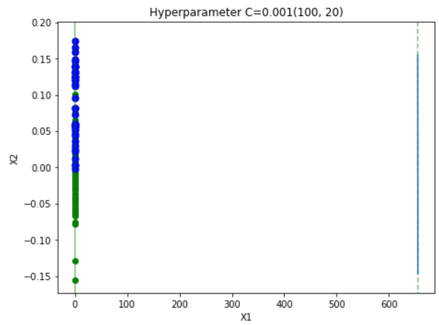
```
def drawSV(X,y,X_n,X_p,k,reg,w,icpt,mini,maxi,i,sup_vec):
    plt.subplot(4,len(reg),k)
    plt.scatter(X_n[:,0],X_n[:,1],color='red',label=reg[b])
    plt.scatter(X_p[:,0],X_p[:,1],color='green',label=reg[b])
    draw_line(w[0],icpt,mini,maxi)
    plt.title("Hyperparameter C="+str(reg[b])+str(i))
    plt.xlabel('X1')
    plt.ylabel('X2')
    ax = plt.gca()
    lim_x = ax.get_xlim() # x-axis limits in data coordinates.
    lim_y=ax.get_ylim() # y-axis limits in data coordinates.
##https://towardsdatascience.com/support-vector-machines-explained-with-python-
examples-cb65e8172c85
    axx = np.linspace(lim_x[0], lim_x[1])
    #x.min(),y.max()
    ayy = np.linspace(lim_y[0], lim_y[1])
    #y.min(), y.max()
    ZY, ZX = np.meshgrid(ayy, axx)
    xy = np.vstack([ZX.ravel(), ZY.ravel()]).T
    Z = Svc.decision_function(xy).reshape(ZX.shape)
##https://scikit-learn.org/stable/auto_examples/svm/plot_separating_hyperplane.
html
    ax.contour(ZX, ZY, Z, colors='g', levels=[-1, 0, 1], alpha=0.5,linestyles=[
'--', '-', '--'])

    plt.scatter(sup_vec[:,0],sup_vec[:,1],s=50,color="blue",label='support vect
ors')
```

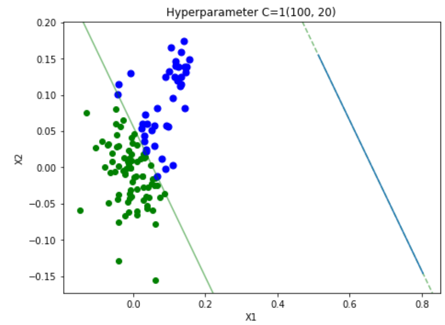
In [35]:
```
ratios = [(100,2), (100, 20), (100, 40), (100, 80)]
reg= [0.001, 1, 100]
for ix,i in enumerate(ratios):
    plt.figure(figsize=(25,25))
    X_p=np.random.normal(0,0.05,size=(i[0],2))
    X_n=np.random.normal(0.13,0.02,size=(i[1],2))
    y_p=np.array([1]*i[0]).reshape(-1,1)
    y_n=np.array([0]*i[1]).reshape(-1,1)
    X=np.vstack((X_p,X_n))
    y=np.vstack((y_p,y_n))
    for b in range(len(reg)):
        Svc=SVC(kernel="linear",C=reg[b],random_state=42)
        Svc.fit(X,y)
        minu,maxi=  X[:,0].min() , X[:,0].max()
        ix=ix+1
        w ,icpt , sup_vec =Svc.coef_ ,Svc.intercept_ ,Svc.support_vectors_
        line_SV = drawSV(X,y,X_n,X_p,ix,reg,w,icpt,minu,maxi,i,sup_vec)
```

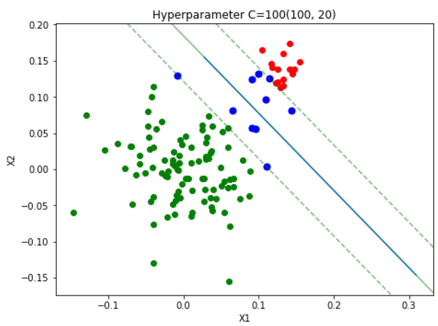

Hyperparameter C=0.001(100, 2)
X1
X2

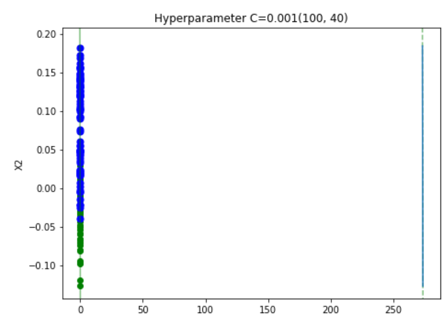

Hyperparameter C=1(100, 2)
X1
X2

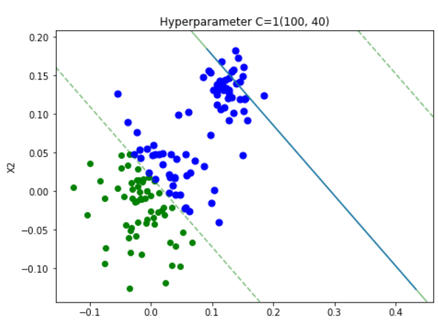

Hyperparameter C=100(100, 2)
X1
X2

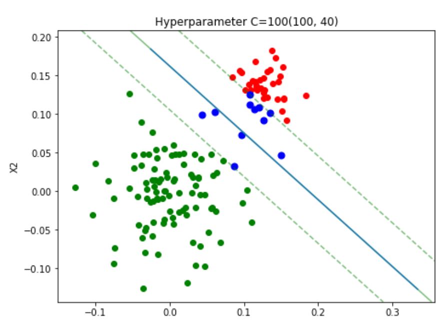

Hyperparameter C=0.001(100, 20)
X1
X2

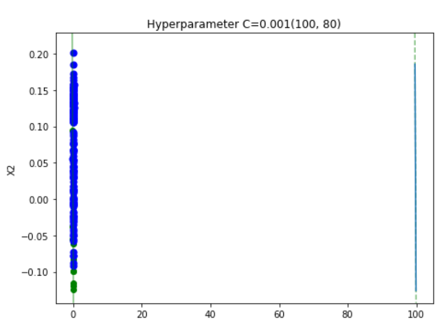

Hyperparameter C=1(100, 20)
X1
X2

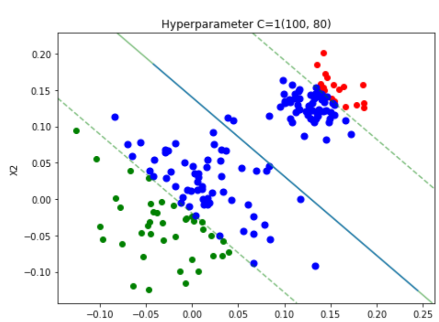

Hyperparameter C=100(100, 20)
X1
X2

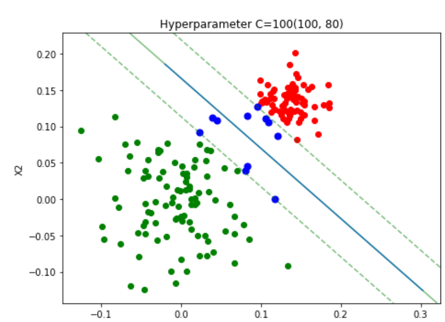

Hyperparameter C=0.001(100, 40)
X1
X2


Hyperparameter C=1(100, 40)
X1
X2


Hyperparameter C=100(100, 40)
X1
X2


Hyperparameter C=0.001(100, 80)
X1
X2


Hyperparameter C=1(100, 80)
X1
X2


Hyperparameter C=100(100, 80)
X1
X2

1.C is a hyper parameter which is inverse of regularization strength.

2.when C=0.001 the decision boundary is not properly formed.

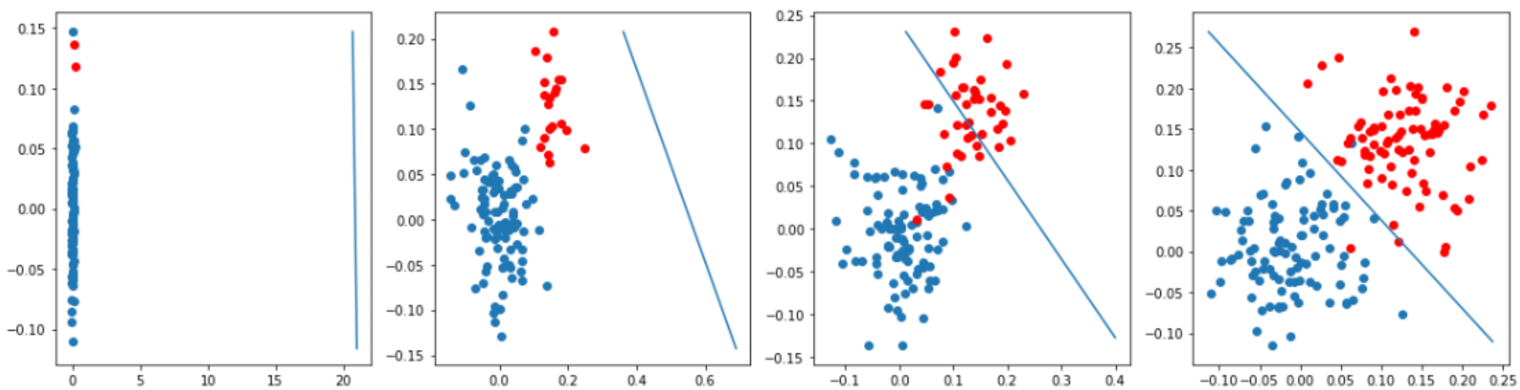
3.when C=100 the Decision boundary is fitted perfectly.

4.when C=1 the decision boundary is overfitted.

Task 2: Applying LR

you will do the same thing what you have done in task 1.1, except instead of SVM you apply [logistic regression (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)

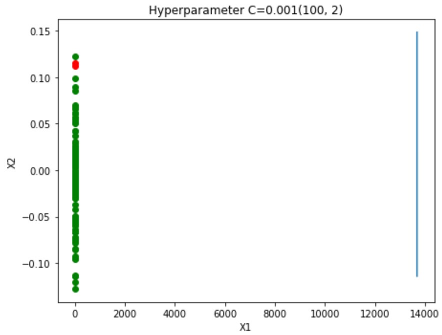
these are results we got when we are experimenting with one of the model

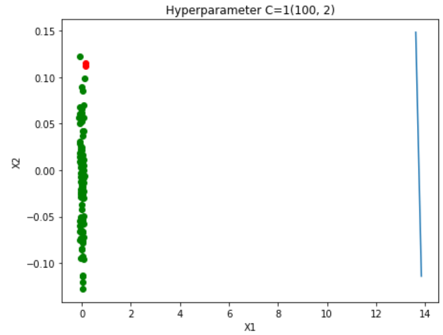


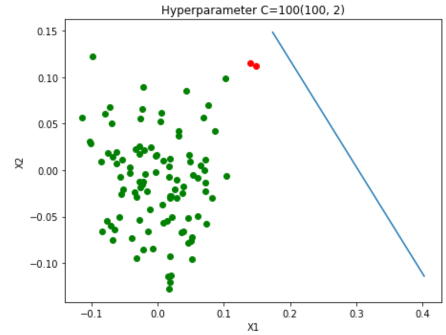
In [32]:
```
def draw(X_n,X_p,f,reg,w,icpt,mini,maxi,i):
    plt.subplot(4,len(reg),f)
    plt.scatter(X_n[:,0],X_n[:,1],color='red')
    plt.scatter(X_p[:,0],X_p[:,1],color='green')
    draw_line(w[0],icpt,mini,maxi)
    plt.title("Hyperparameter C="+str(reg[b])+str(i))
    plt.xlabel('X1')
    plt.ylabel('X2')
```

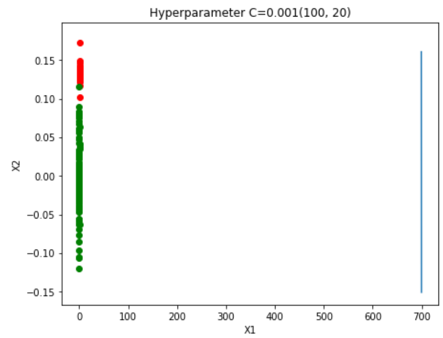
In [33]:

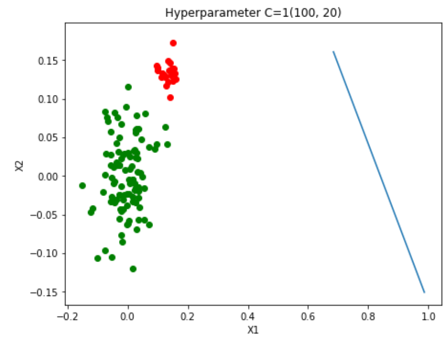
```
ratios = [(100,2), (100, 20), (100, 40), (100, 80)]
reg= [0.001, 1, 100]
for idx,i in enumerate(ratios):
    plt.figure(figsize=(24,25))
    X_p=np.random.normal(0,0.05,size=(i[0],2))
    X_n=np.random.normal(0.13,0.02,size=(i[1],2))
    y_p=np.array([1]*i[0]).reshape(-1,1)
    y_n=np.array([0]*i[1]).reshape(-1,1)
    X=np.vstack((X_p,X_n))
    y=np.vstack((y_p,y_n))
    for b in range(3):
        Lr=LogisticRegression(C=reg[b],random_state=42)
        Lr.fit(X,y)
        minu,maxi=X[:,0].min() , X[:,0].max()
        w ,icpt =Lr.coef_ ,Lr.intercept_
        idx=idx+1
        line=draw(X_n,X_p,idx,reg,w,icpt,minu,maxi,i)
```

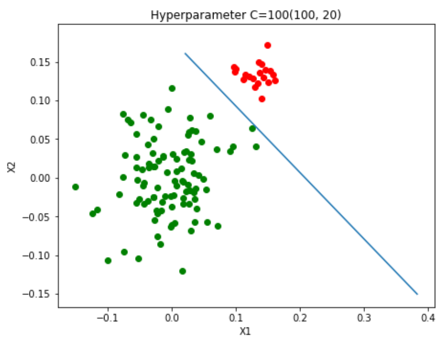

Hyperparameter C=0.001(100, 2)
X2
X1

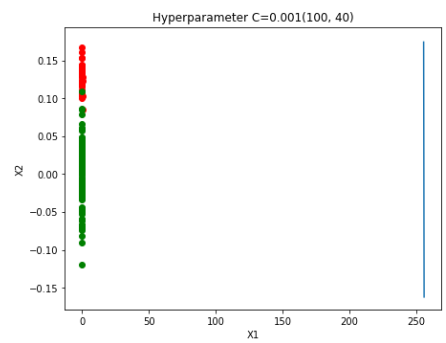

Hyperparameter C=1(100, 2)
X2
X1

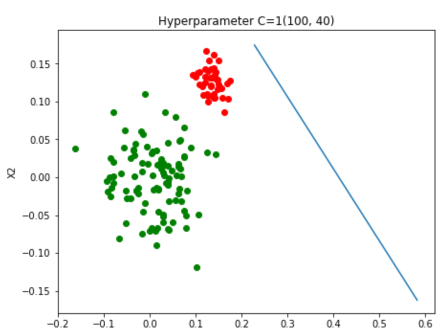

Hyperparameter C=100(100, 2)
X2
X1

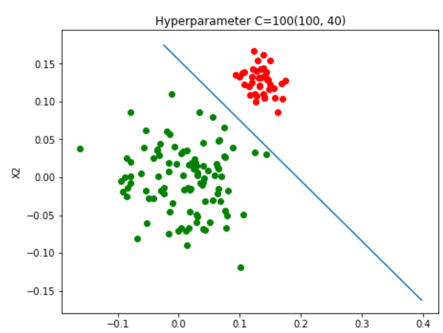

Hyperparameter C=0.001(100, 20)
X2
X1

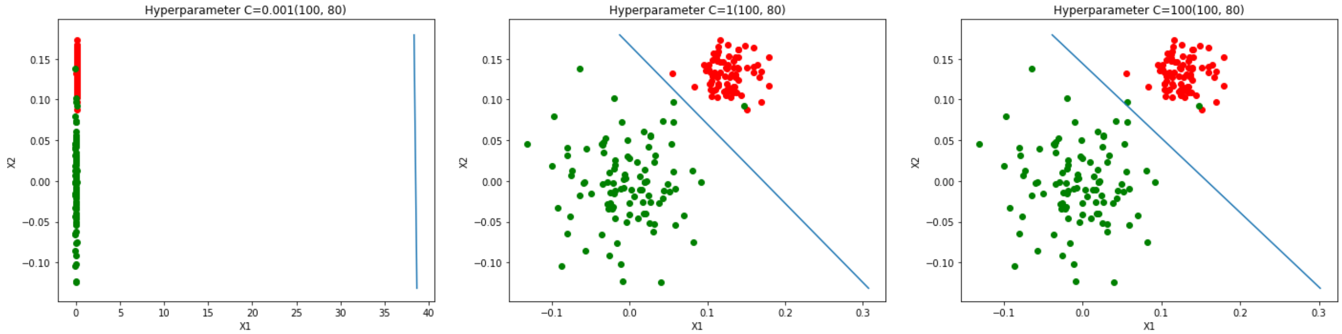

Hyperparameter C=1(100, 20)
X2
X1


Hyperparameter C=100(100, 20)
X2
X1


Hyperparameter C=0.001(100, 40)
X2
X1


Hyperparameter C=1(100, 40)
X2
X1


Hyperparameter C=100(100, 40)
X2
X1



c is inverse of regularization strength.

when C is less there is high tendency of underfitting the data

when C is large there is a tendency of overfitting the data.

when C=0.001 the decision boundary is not formed properly.

when C=100 we can see the decision boundary clearly separates the positive and the negative points.

pic_1.jpg