8_A

Importing libraries

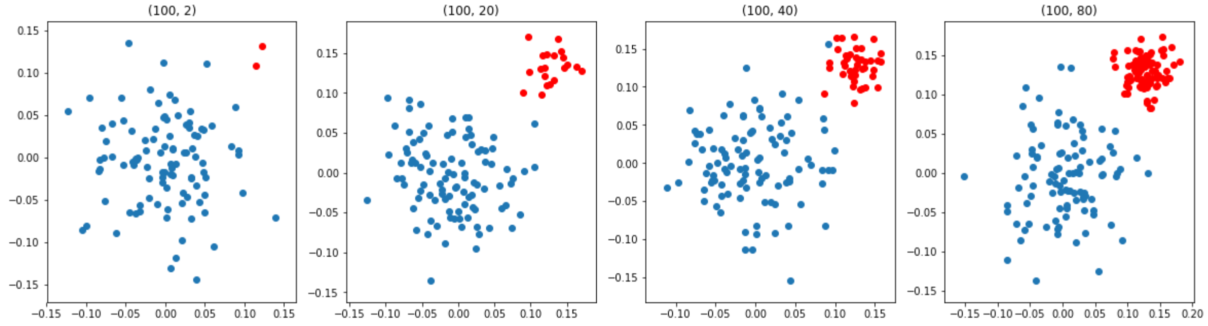
In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import SGDClassifier
from sklearn.linear_model import LogisticRegression
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, Normalizer
import matplotlib.pyplot as plt
from sklearn.svm import SVC
import warnings
warnings.filterwarnings("ignore")
from IPython.display import Image as img
```

In [2]:
```
def draw_line(coef,intercept, mi, ma): # FUCTION TO DRAW SEPERATING PLA
NE
    points=np.array([[((-coef[1]*mi - intercept)/coef[0]), mi],[((-coef
[1]*ma - intercept)/coef[0]), ma]])
    plt.plot(points[:,0], points[:,1])
```

Creating 2d imbalanced data points

In [3]:
```
ratios = [(100,2), (100, 20), (100, 40), (100, 80)] #CREATING DATA BASE
D ON THESE TUPLE RATIOS
plt.figure(figsize=(20,5))
for j,i in enumerate(ratios):
    plt.subplot(1, 4, j+1)
    plt.title(str(i))
```

```
    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()
```

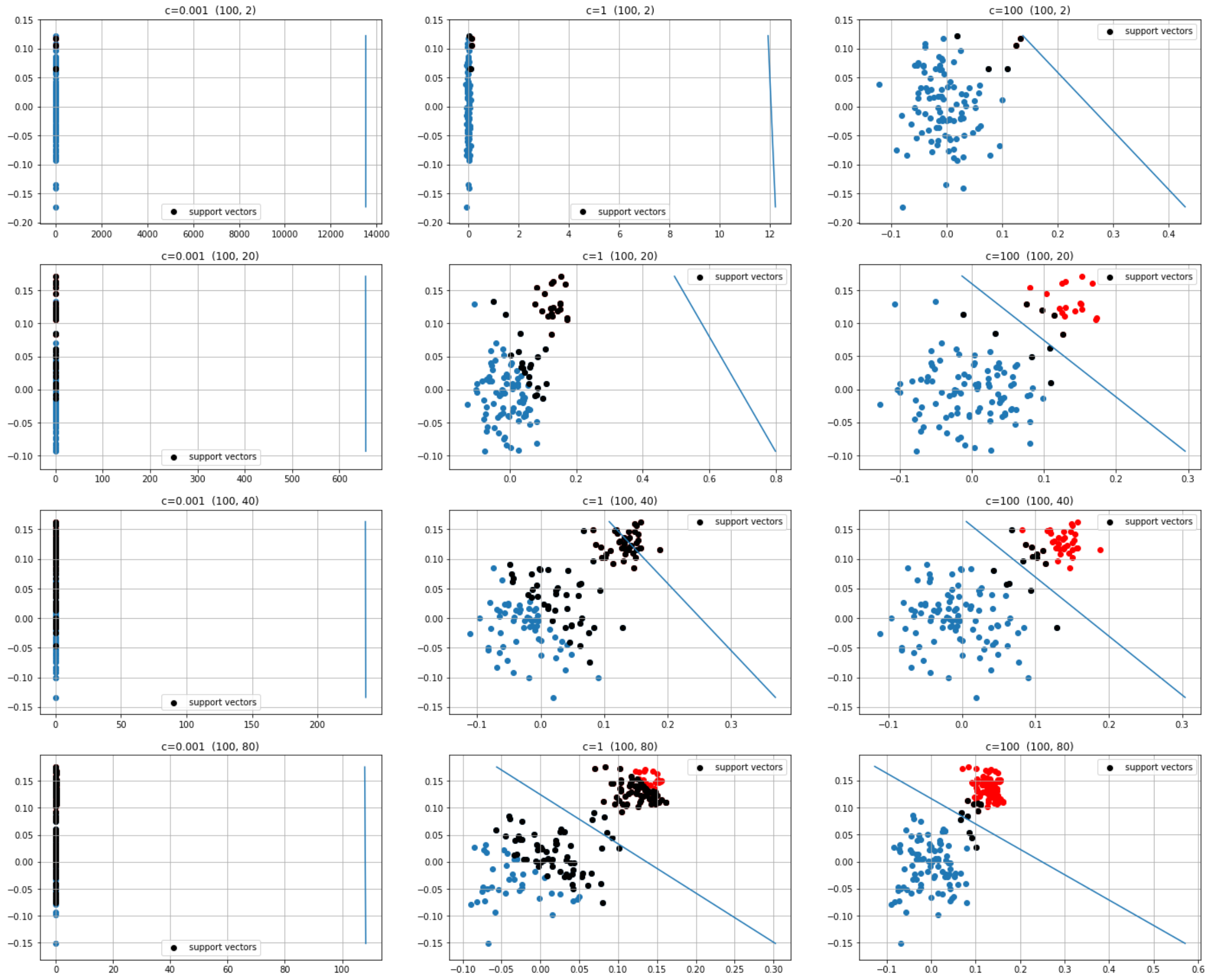


Task 1: Applying SVM

In [4]:

```
np.random.seed(15)
s=0
ratios = [(100,2), (100, 20), (100, 40), (100, 80)]
rate= [0.001, 1, 100]
plt.figure(figsize=(24,20))
for j,i in enumerate(ratios):
    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 k in range(3):
```

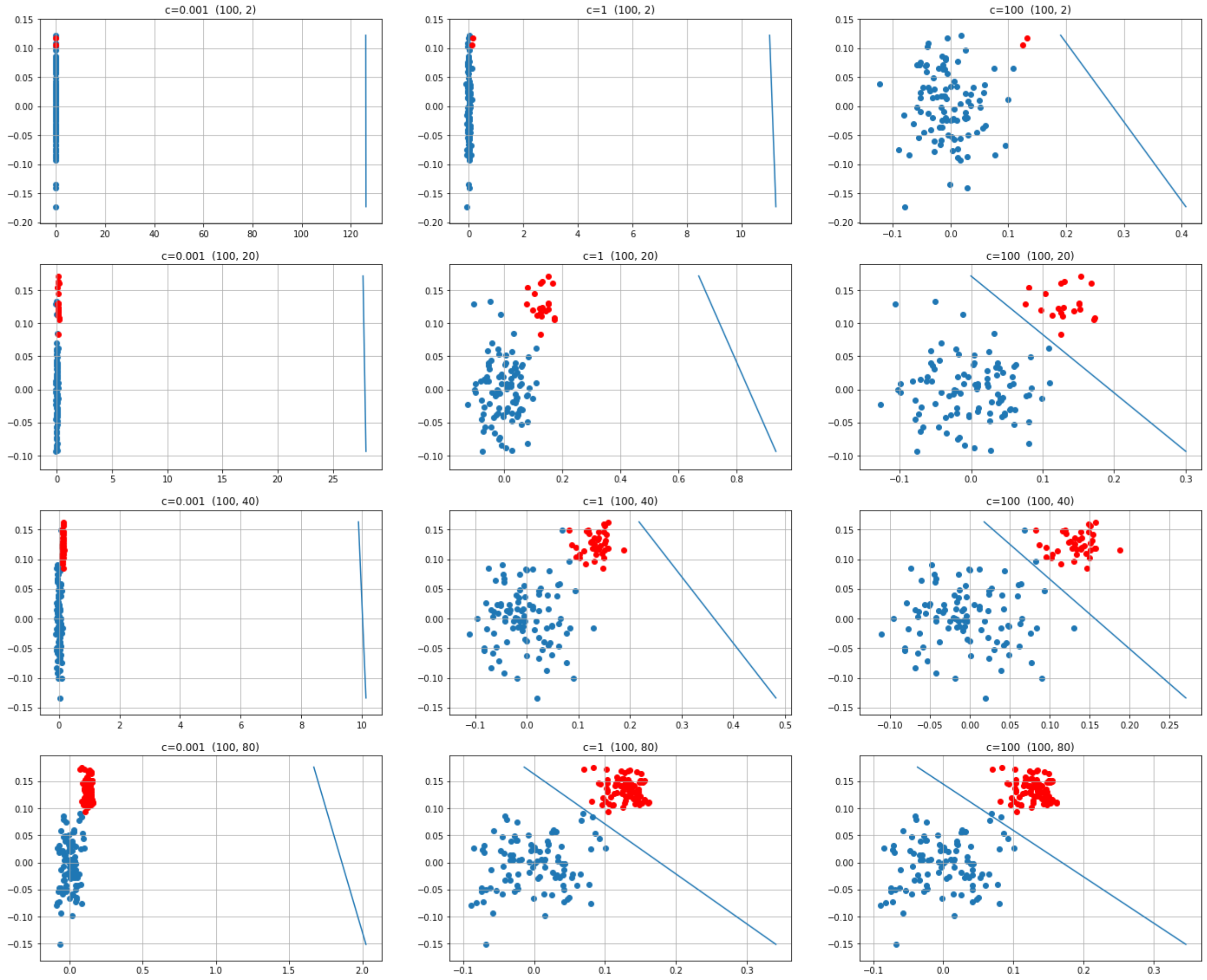
```
        s=s+1
        plt.subplot(4,3,s)
        plt.title("c="+str(rate[k])+"  "+str(i))
        plt.grid()
        plt.scatter(X_p[:,0],X_p[:,1])
        plt.scatter(X_n[:,0],X_n[:,1],color='red')
        clf=SVC(kernel="linear",C=rate[k],random_state=15)
        clf.fit(X,y)  # GETTING THE INTERCEPT AND WEIGHT COEFFICIENT
        weight=clf.coef_
        intercept=clf.intercept_
        sv=clf.support_vectors_

        plt.scatter(sv[:,0],sv[:,1],color="black",label='support vector
s')
        plt.legend()
        mi=min(X[:,1])
        mx=max(X[:,1])
        draw_line(weight[0],intercept,mi,mx)
```



Task 2: Applying LR

In [17]:
```
np.random.seed(15)
s=0
ratios = [(100,2), (100, 20), (100, 40), (100, 80)]
rate= [0.001, 1, 100]
plt.figure(figsize=(24,20))
```

```
for j,i in enumerate(ratios):
    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 k in range(3):
        s=s+1
        plt.subplot(4,3,s)
        plt.title("c="+str(rate[k])+"  "+str(i))
        plt.grid()
        plt.scatter(X_p[:,0],X_p[:,1])
        plt.scatter(X_n[:,0],X_n[:,1],color='red')
        clf = LogisticRegression(C=rate[k],random_state=15)
        clf.fit(X,y)
        weight=clf.coef_
        intercept=clf.intercept_
        mi=min(X[:,1])
        mx=max(X[:,1])
        draw_line(weight[0],intercept,mi,mx)
```



Observations

- Both svm and lr c is a hyper parameter which is inverse of regularization strength.
- so the regularization discourages learning complex functions ,to avoid the risk of overfitting
- as c decreases regularization strength increases and it moves to underfit ,it will consider all points as single class

- as c increases regularization strength decreases it tries to reduce underfitr and it tries to recognize dataset has 2 classes
- at larger c(c=100) regularization has only small effect,it will do correct fitting and leads to overfitting

sum explanation

$$w^* b^* = \underset{w,b}{\arg\min} \frac{\|w\|}{2} + C \times \frac{1}{n} \sum_{i=1}^{n} \xi_i$$

1) as $C \uparrow$ (increases)

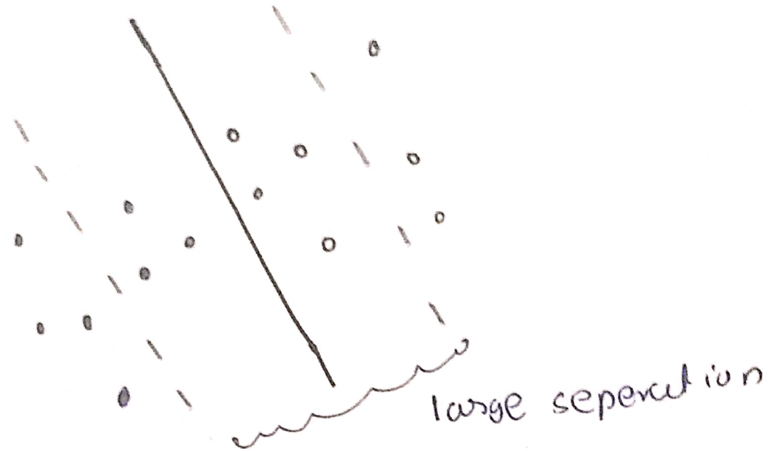
small seperation

- the seperation b/w the plane decreases, average distance of mis-classification decreases

as a Result

- works very well in Train data
- leads to overfit.
- not a smooth decision curve.

(2) as c ↓ (decreases)



- as c decreases more preference to $\frac{||w||}{2}$ term and seperation b/w the plane increases.

- As a result
  - moves to under fit
  - Smooth decision curve.