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1 Behaviour of Linear Models

1.1 Imports

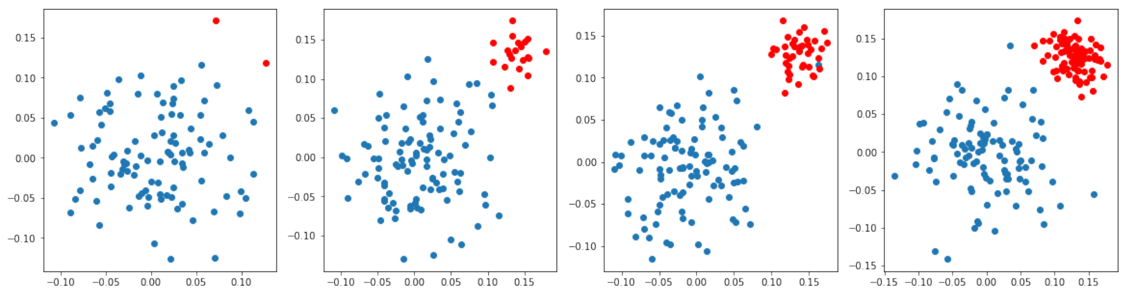
[12]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import SGDClassifier
from sklearn.linear_model import LogisticRegression
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, Normalizer
import matplotlib.pyplot as plt
from sklearn.svm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

# Fixing the seed value to obtain same resutls throughout
np.random.seed(seed=42)
```

1.2 Defining Reusable Functions

[13]:
```
def draw_line(coef,intercept, mi, ma,ax):
    # 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␣
↪here 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␣
↪here 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]])
    ax.plot(points[:,0], points[:,1], color='green')
```

1.3 What if Data is imabalanced

[17]:
```
# 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()
```



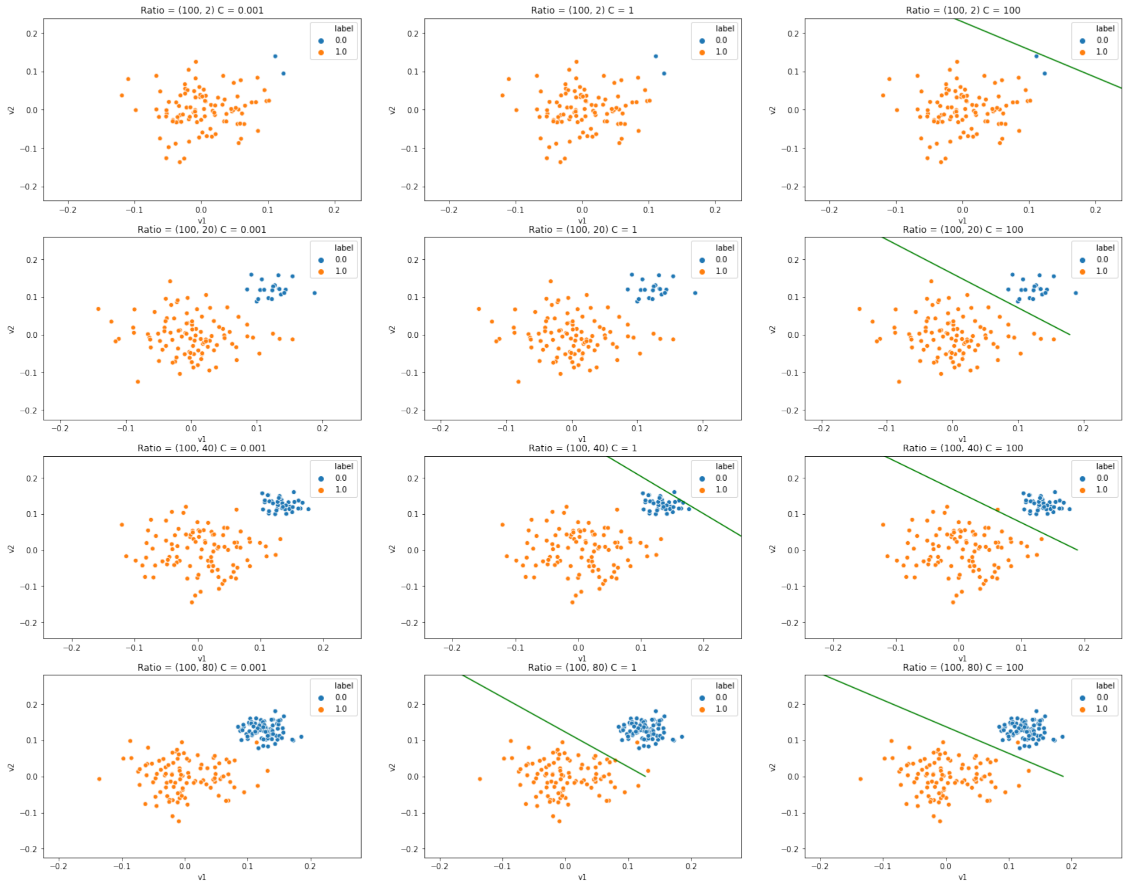
your task is to apply SVM (sklearn.svm.SVC) and LR (sklearn.linear_model.LogisticRegression) with different regularization strength [0.001, 1, 100]

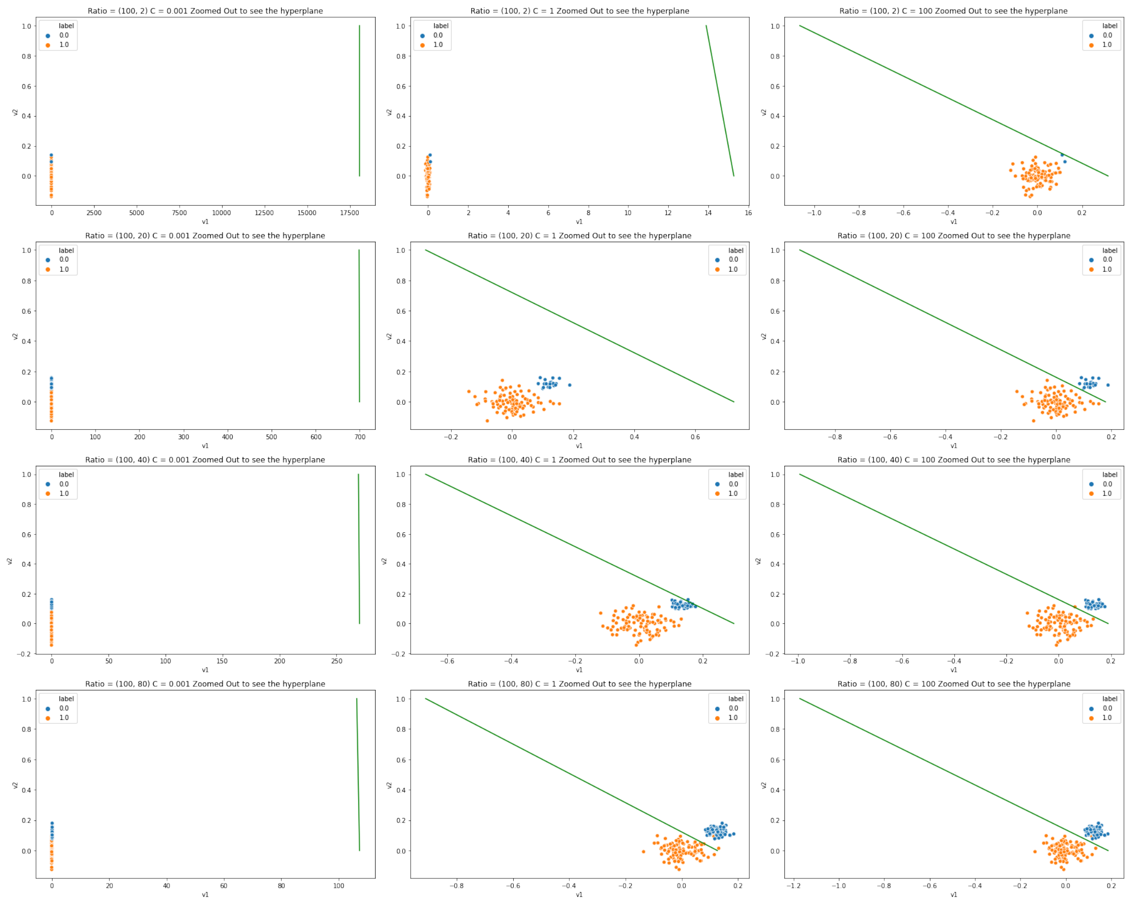
1.4 Task 1: Applying SVM

1.4.1 Linear SVM Implementation

[19]:
```
_, ax = plt.subplots(4,3, figsize=(25,20))
_, ax1 = plt.subplots(4,3, figsize=(25,20))
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_train=np.vstack((X_p,X_n))
    y_train=np.vstack((y_p,y_n))

    # Creating dataframe for plptting purpose
    df = pd.DataFrame(np.hstack((x_train,y_train)),columns=['v1','v2','label'])
```

```
# Hyperparameter Tuning
for ind, param in enumerate([0.001, 1, 100]):
    # Training the model
    clf = SVC(C=param, kernel='linear',random_state=42)
    clf.fit(x_train, y_train)
    # Plotting the scatter plot
    sns.scatterplot('v1', 'v2', hue='label', data=df, ax=ax[j][ind])
    sns.scatterplot('v1', 'v2', hue='label', data=df, ax=ax1[j][ind])
    # Drawing the hyper plane.
    draw_line(clf.coef_[0], clf.intercept_[0], min(df['label']),␣
↪max(df['label']), ax[j][ind])
    draw_line(clf.coef_[0], clf.intercept_[0], min(df['label']),␣
↪max(df['label']), ax1[j][ind])
    # Limiting the plot so that values could be seen properly
    ax[j][ind].set_ylim(min(x_train[:,1])-0.1,max(x_train[:,1])+0.1)
    ax[j][ind].set_xlim(min(x_train[:,1])-0.1,max(x_train[:,1])+0.1)
    # Setting heading for each plot
    ax[j][ind].set_title('Ratio = {} C = {}'.format(i, param))
    # Setting x_label and y_label for each plot
    ax[j][ind].set_xlabel = df['v1'].values
    ax[j][ind].set_ylabel = df['v2'].values
    ax1[j][ind].set_title('Ratio = {} C = {} Zoomed Out to see the␣
↪hyperplane'.format(i, param))
    # Setting x_label and y_label for each plot
    ax1[j][ind].set_xlabel = df['v1'].values
    ax1[j][ind].set_ylabel = df['v2'].values
    plt.tight_layout()
```


Ratio = (100, 2) C = 0.001
Ratio = (100, 2) C = 1
Ratio = (100, 2) C = 100
Ratio = (100, 20) C = 0.001
Ratio = (100, 20) C = 1
Ratio = (100, 20) C = 100
Ratio = (100, 40) C = 0.001
Ratio = (100, 40) C = 1
Ratio = (100, 40) C = 100
Ratio = (100, 80) C = 0.001
Ratio = (100, 80) C = 1
Ratio = (100, 80) C = 100
label
0.0
1.0
v1
v2



Note: - Created zoomed in and zoomed out version of plots.

- If you traverse the grid horizontally the class ratio remains same and hyper parameter values change only.
- If you traverse the grid vertically the class ratio value changes and hyper parameter values remain same.

1.4.2 Oberservations on Linear SVM Implementation Outcome

- **For ratio 100:2**

  Since the number of datapoints for class 0 is very less hence in the optimization problem there are lesser constraints regrading the data points of class 0.This leads to optimization problem give weights and biases which are optimized for class 1 data points

  - **C=0.001**

    Reguralization Hyperparameter value is small => higher chance of underfitting as the cost/penalty of making mistakes is prettylow. Hence the (weights) normal vector to the hyperplane has such high values.

  - **C = 1**

Reguralization Hyperparameter value is pretty high. => lesser chance of underfitting as the cost/penalty of making mistakes is pretty high.

- **C = 100**

  Reguralization Hyperparameter value is very high => Much higher cost/penalty of making mistakes.

- **Summary**
  - Due to so high data imabalance that the model is always underfitting as there are lesser constraints on the optimzation problem.
  - If such scenarios occur, then even for a small mistake the model should have high cost/penalty

- **For ratio 100:20**

  A bit better ratio of data is helping the model to put much better contraints on the optimization problem.

  - **C = 0.001**

    Here again the hyperplane is far from the actual datapoint meaning it is still classifying the data points of class 0 as 1 , this is due to factor that cost/penalty on optimization for making mistakes is way too low.

  - **C = 1**

    Here still the hyperplane/model does not identifies the class 0 points but it is much closer to the data point clusters due to high regularization.

  - **C = 100**

    Due to very high cost/penalty/regualrization factor the model is pretty much correclty classfiying the data points.

- **Summary** Due to high 100:20 imbalance is pretty high hence using very strict regularization on the optimization problem helps in correct classification of data points.

- **For ratio 100:40** A much better class ratios will need lesser penalty as there are greater number of constraints on the optimization problem.
  - **C=0.001**
    * Too low of penalty is not helping the model.
  - **C = 1**
    * With slight increase in regularization factor the model can fairly well distinguish betweem the different class with some errors.
  - **C = 100**
    * Due to very high penalty the model works very well.

- **Summary** Due to high 100:40 imbalance is pretty less hence using moderate regularization on the optimization problem helps in correct classification of data points.

- **For ratio 100:80**
  - **C=0.001**
    * Too low of penalty is not helping the model.

- **C = 1**
  * Here the model works perfectly well.
- **C = 100**
  * Mot much change in the model and the model works perfectly well.

- **Summary** Due to high 100:80 imbalance is very low hence using moderate regularization on the optimization problem helps in correct classification of data points.

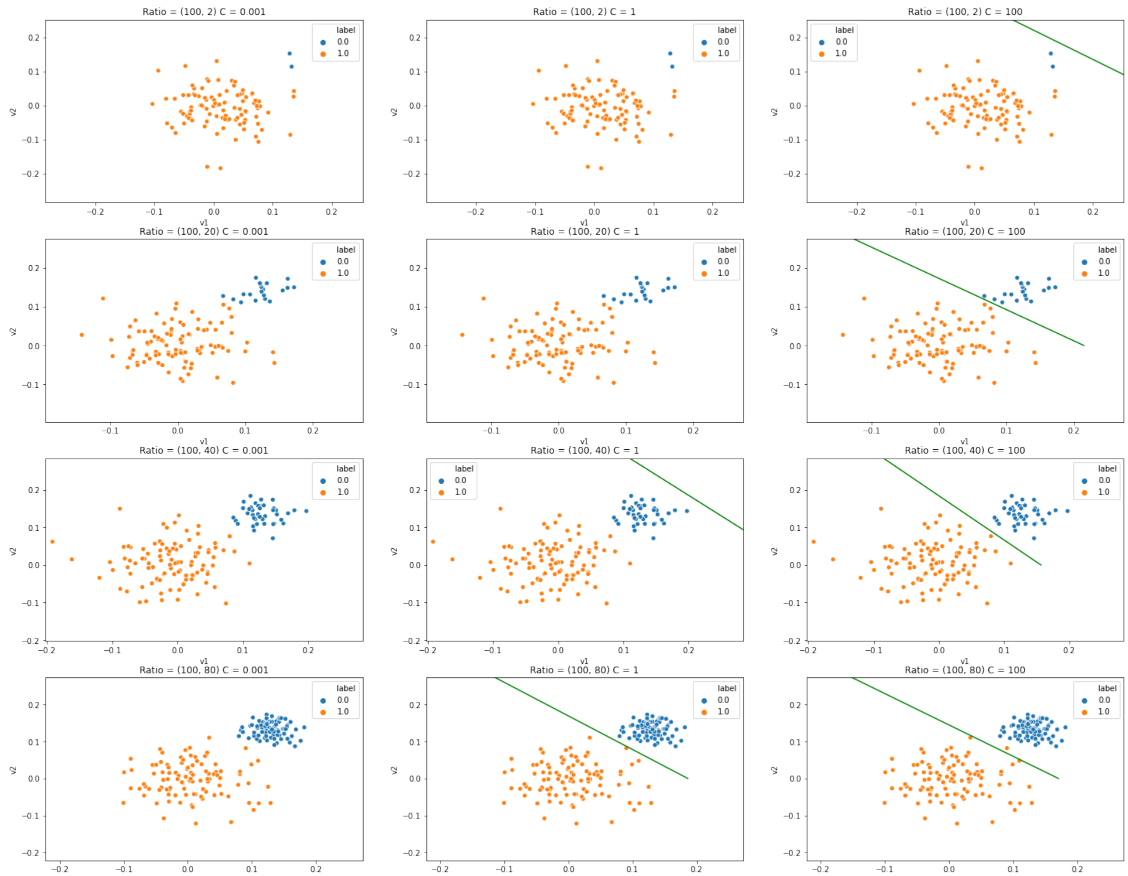
1.5 Task 2: Applying LR

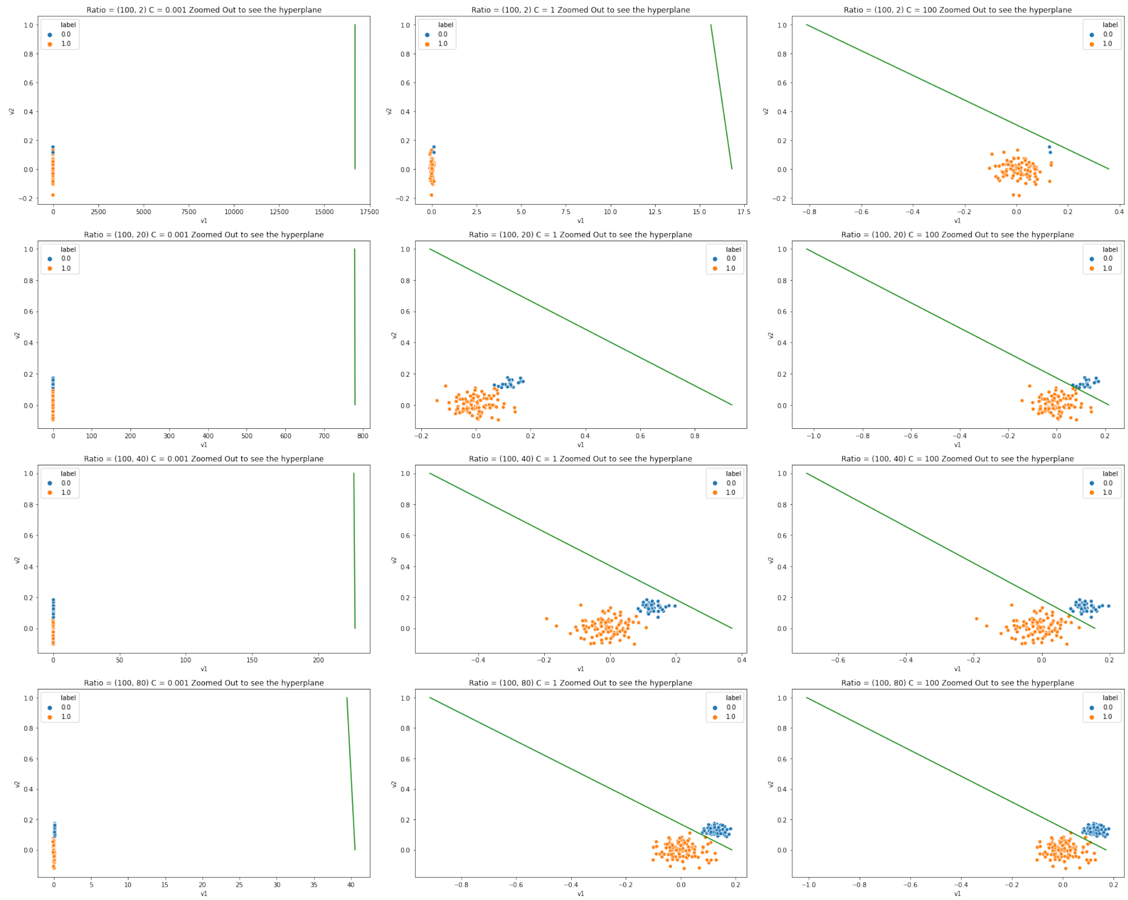
you will do the same thing what you have done in task 1.1, except instead of SVM you apply logistic regression

1.5.1 Logistic Regression Implementation

[21]:
```
_, ax = plt.subplots(4,3, figsize=(25,20))
_, ax1 = plt.subplots(4,3, figsize=(25,20))
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_train=np.vstack((X_p,X_n))
    y_train=np.vstack((y_p,y_n))

    # Creating dataframe for plptting purpose
    df = pd.DataFrame(np.hstack((x_train,y_train)),columns=['v1','v2','label'])

    # Hyperparameter Tuning
    for ind, param in enumerate([0.001, 1, 100]):
        # Training the model
        clf = LogisticRegression(C=param, random_state=42)
        clf.fit(x_train, y_train)
        # Plotting the scatter plot
        sns.scatterplot('v1', 'v2', hue='label', data=df, ax=ax[j][ind])
        sns.scatterplot('v1', 'v2', hue='label', data=df, ax=ax1[j][ind])
        # Drawing the hyper plane.
        draw_line(clf.coef_[0], clf.intercept_[0], min(df['label']),␣
 ↪max(df['label']), ax[j][ind])
        draw_line(clf.coef_[0], clf.intercept_[0], min(df['label']),␣
 ↪max(df['label']), ax1[j][ind])
        # Limiting the plot so that values could be seen properly
        ax[j][ind].set_ylim(min(x_train[:,1])-0.1,max(x_train[:,1])+0.1)
        ax[j][ind].set_xlim(min(x_train[:,1])-0.1,max(x_train[:,1])+0.1)
        # Setting heading for each plot
        ax[j][ind].set_title('Ratio = {} C = {}'.format(i, param))
        # Setting x_label and y_label for each plot
        ax[j][ind].set_xlabel = df['v1'].values
```

```
        ax[j][ind].set_ylabel = df['v2'].values
        ax1[j][ind].set_title('Ratio = {} C = {} Zoomed Out to see the␣
↪hyperplane'.format(i, param))
        # Setting x_label and y_label for each plot
        ax1[j][ind].set_xlabel = df['v1'].values
        ax1[j][ind].set_ylabel = df['v2'].values
        plt.tight_layout()
```





Note: - Created zoomed in and zoomed out version of plots.

- If you traverse the grid horizontally the class ratio remains same and hyper parameter values change only.
- If you traverse the grid vertically the class ratio value changes and hyper parameter values remain same.

1.5.2 Observation on Logistic Regression Outcome

- **For ratio 100:2**

  The current imabalance is too low

  - **C = 0.001**

    Since the model has very low penalty on weight vectors hence the model will have small absoulte derivative values which would in turn lead to high absoulte weight values and hence the hyperplane would do missclassification as minority datapoints are pretty less

  - **C = 1**

    Since the model has moderate penalty on weight vectors hence the model will have weight vectors a bit less towards the dominant classes and would also try to classify the minority classes . Even though it fails to do so but we can see that it has bent towards the datapoints.

- **C = 100**

  Since the model has very high penalty on weight vectors hence the model will have weight vectors which .wil lincur heavy penalties and due to which the dervative absolute value will become higher and the hyperplane will tend towards the miinority classes also. Here we see that hyperplane **almost touches the minority class datapoints** , but , due to very high iabalance in data it is not able to do so

- **For ratio 100:20**

  The current imbalance is low. But since the class imabalance is much less than previous case notice the **x axis** values , here the hyperplane is **much closer** to the datapoints than in the previous case with same hyperparameters.

  - **C = 0.001**

    Since the model has very low penalty on weight vectors hence the model will have weight vectors of very high absolute value in the favour of dominant classes.

  - **C = 1**

    Higher penalty due to high hyperparameter value hence the model is **almost close** to the data points.

  - **C = 100**

    Since Very high penalty the model here classifies the different **classes correctly**.

- **For ratio 100:40**

  The current imbalance okay. But since the class imabalance is much less than previous case notice the **x axis** values , here the hyperplane is **much more closer** to the datapoints than in the previous case with same hyperparameters.

  - **C = 0.001**

    Since the model has very low penalty on weight vectors hence the model will have weight vectors of moderatly high absolute value in the favour of dominant classes.

  - **C = 1**

    Higher penalty due to high hyperparameter value hence the model is **very close** to the data points.

  - **C = 100**

    Since Very high penalty the model here classifies the different classes **almost correctly**.

- **For ratio 100:80**

  The current imbalance good. But since the class imabalance is much less than previous case notice the **x axis** values , here the hyperplane is **much more closer** to the datapoints than in the previous case with same hyperparameters.

- **C = 0.001**

  Since the model has very low penalty on weight vectors hence the model will have weight vectors of okay absolute value in the favour of dominant classes.

- **C = 1**

  The hyperplane can **easily seperate** the classes.

- **C = 100**

  Since Very high penalty the model here classifies the different classes but makes a mistake of classifiying dominant class as minor class.