8A_LR_SVM

November 18, 2020

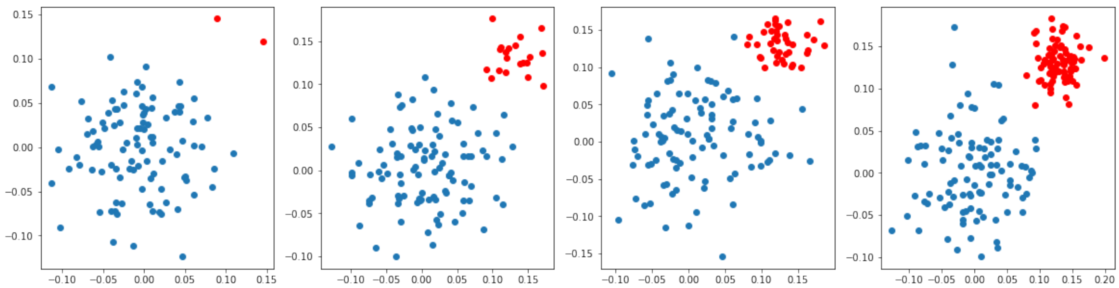
1 Linear-Models - What if Data is imabalanced?

[1]:
```
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")
```

[2]:
```
def draw_line(coef,intercept, mi, ma):

    ''' mi, ma ==> ax+by+c=0 ==> x = (-by-c)/a '''

    points=np.array([[((-coef[1]*mi - intercept)/coef[0]), mi],[((-coef[1]*ma -␣
↪intercept)/coef[0]), ma]])
    plt.plot(points[:,0], points[:,1])
```

2 What if Data is imabalanced

[3]:
```
# 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()
```

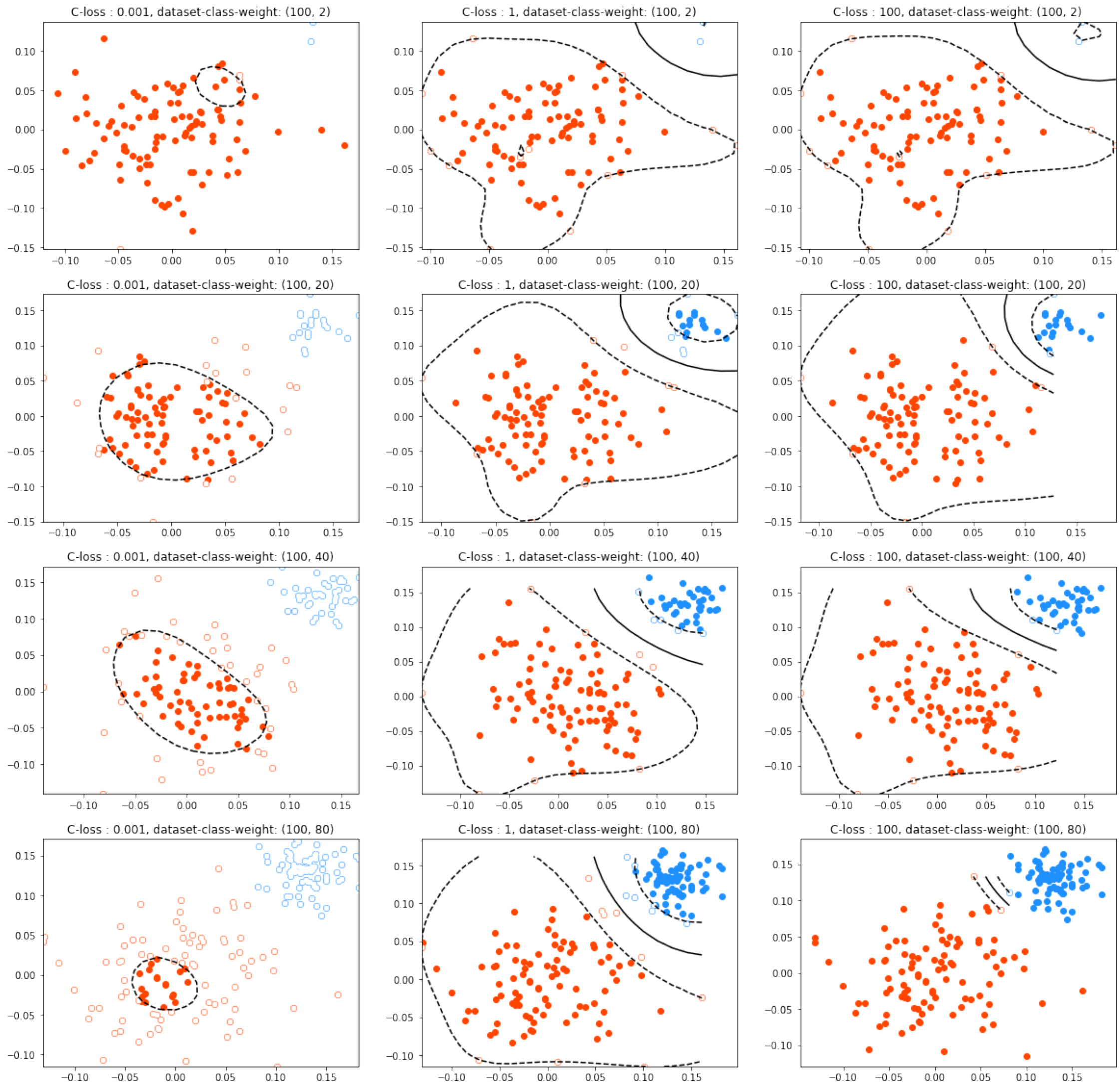


your task is to apply SVM (sklearn.svm.SVC) and LR (sklearn.linear_model.LogisticRegression) with different regularization strength [0.001, 1, 100]

2.1 Task 1: Applying SVM

[4]:
```
from sklearn.svm import SVC
hypers = [0.001, 1, 100]

plt.figure(figsize=(20, 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 c, k in enumerate(range(3*j+1, 3*(j+1)+1)):

        clf = SVC(C=hypers[c])
        clf.fit(X, y)

        f1 = clf.support_vectors_[:,0]
        f2 = clf.support_vectors_[:,1]

        f1_low, f1_max = f1.min(), f1.max()
        f2_low, f2_max = f2.min(), f2.max()

        xx = np.linspace(f1_low, f1_max, 20)
        yy = np.linspace(f2_low, f2_max, 20)
```

```
        X1, X2 = np.meshgrid(xx, yy)

        Z = np.empty(X1.shape)
        for (y_, z), val in np.ndenumerate(X1):
            x1 = val
            x2 = X2[y_, z]
            p = clf.decision_function([[x1, x2]])
            Z[y_, z] = p[0]

        levels = [-1, 0.0, 1]
        linestyles = ['dashed', 'solid', 'dashed']

        plt.subplot(4, 3, k)
        plt.scatter(X_p[:,0],X_p[:,1], color='orangered')
        plt.scatter(X_n[:,0], X_n[:,1], color='dodgerblue')
        plt.scatter(f1, f2,s=25, color="white")
        plt.contour(X1, X2, Z, levels, colors='k', linestyles=linestyles,␣
 ↪alpha=1)
        plt.title("C-loss : " + str(hypers[c])+", dataset-class-weight:␣
 ↪"+str(i))
plt.show()
```



2.1.1 OBSERVATION:

1. When HingeLoss(C) is very low c = 0.001, classifier din't learn all data points properly; (classifier underfits). So, the position of the hyper plane separates negative data points as support vectors.

2. When HingeLoss(C) is very high c=10, classifier has learnt all data points very well; (classifier overfits). So, the position of the hyper plane exactly lies inbetween two classes.

3. when HingeLoss(C) is c=1, it learns properly. so, hyperplanes mostly tries to lie inbetween two classes.

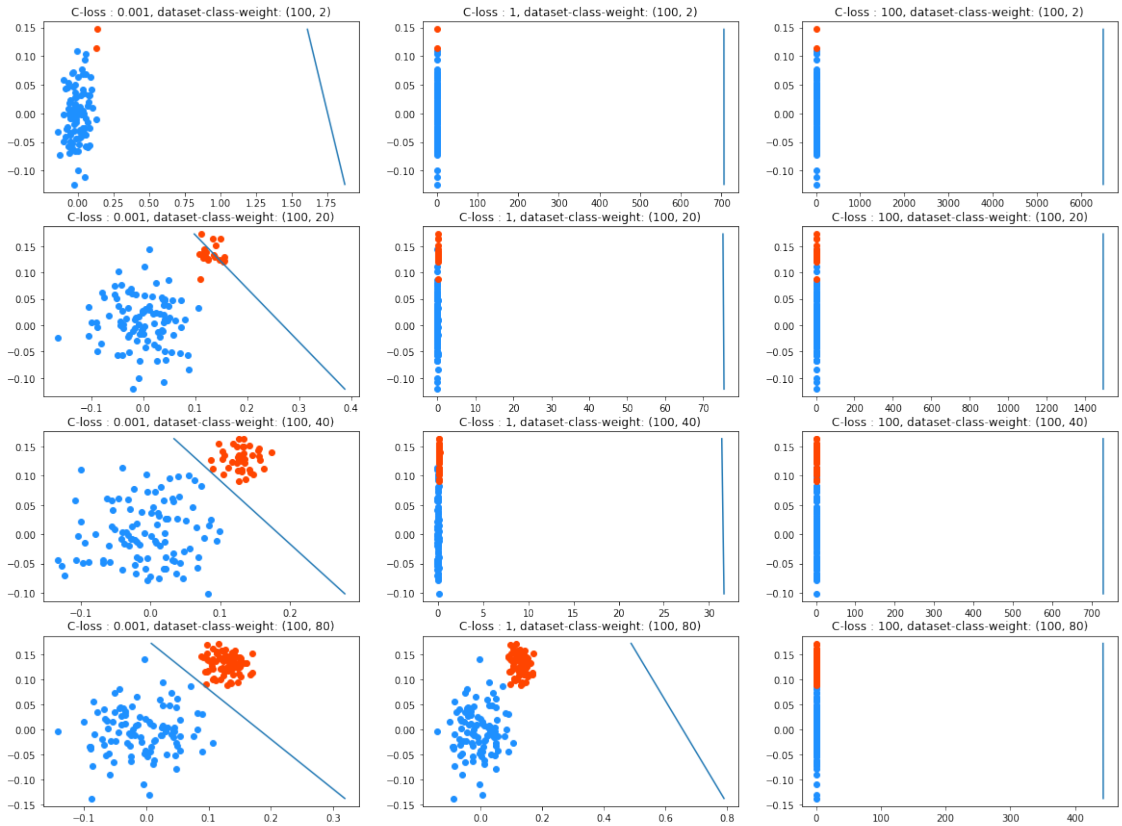
4. when dataset is **too mach imbalanced (100, 2) and irespective of "C",classifier has learnt all negative point as positive**.

```
5. when dataset is imbalanced (100, 20) and c is very low c=0.1, classifier has
learnt all negative point as positive.
```

2.2 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

[5]:
```
# here we are creating 2d imbalanced data points
ratios = [(100,2), (100, 20), (100, 40), (100, 80)]
hypers = [0.001, 1, 100]

fig = plt.figure(figsize=(20, 15));
count=1

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 c, k in enumerate(range(3*j+1, 3*(j+1)+1)):

        log = SGDClassifier(alpha=hypers[c], loss='log').fit(X, y)

        plt.subplot(4, 3, k)
        plt.scatter(X_p[:,0],X_p[:,1], color='dodgerblue')
        plt.scatter(X_n[:,0],X_n[:,1], color='orangered')
        draw_line(log.coef_[0], log.intercept_[0], min(X[:, 1]), max(X[:, 1]))
        plt.title("C-loss : " + str(hypers[c])+", dataset-class-weight:␣
 ↪"+str(i))
fig.show();
```



2.2.1 OBSERVATION:

1. when regulizer **Regulaizer is very low alpha=0.001** and **if the dataset is >= 20%** ((100,20), (100, 40), (100,80)), classifier learning datapoints very well.

2. when dataset is **too much imbalanced (100, 2)** and **regulizer is very low c=0.1**, classifier has learnt nothing. the hyper plane lies somewhere in space.

3. when **regulizer is more than c=1.0**, classifier has learnt nothing. the hyper plane lies somewhere in space.