

8E_F_LR_SVM

January 28, 2020

9E and 9F: Finding the Probability $P(Y=1 | X)$

9E: Implementing Decision Function of SVM RBF Kernel

After we train a kernel SVM model, we will be getting support vectors and their corresponding coefficients α_i

Check the documentation for better understanding of these attributes:

<https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html>

As a part of this assignment you will be implementing the `decision_function()` of kernel SVM, here `decision_function()` means based on the value return by `decision_function()` model will classify the data point either as positive or negative

Ex 1: In logistic regression After training the models with the optimal weights w we get, we will find the value $\frac{1}{1+\exp(-\frac{1}{(wx+b)})}$, if this value comes out to be < 0.5 we will mark it as negative class, else its positive class

Ex 2: In Linear SVM After training the models with the optimal weights w we get, we will find the value of $\text{sign}(wx + b)$, if this value comes out to be -ve we will mark it as negative class, else its positive class.

Similarly in Kernel SVM After training the models with the coefficients α_i we get, we will find the value of $\text{sign}(\sum_{i=1}^n (y_i \alpha_i K(x_i, x_q)) + \text{intercept})$, here $K(x_i, x_q)$ is the RBF kernel. If this value comes out to be -ve we will mark x_q as negative class, else its positive class.

RBF kernel is defined as: $K(x_i, x_q) = \exp(-\gamma ||x_i - x_q||^2)$

For better understanding check this link: <https://scikit-learn.org/stable/modules/svm.html#svm-mathematical-formulation>

0.1 Task E

1. Split the data into $X_{train}(60)$, $X_{cv}(20)$, $X_{test}(20)$
2. Train $SVC(\gamma = 0.001, C = 100.)$ on the (X_{train}, y_{train})
3. Get the decision boundary values f_{cv} on the X_{cv} data i.e. $f_{cv} = \text{decision_function}(X_{cv})$ you need to implement this `decision_function()`

```
In [1]: import numpy as np
import pandas as pd
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
```

```
In [2]: X, y = make_classification(n_samples=5000, n_features=5, n_redundant=2,
                                n_classes=2, weights=[0.7], class_sep=0.7, random_state=15)
```

0.1.1 Pseudo code

```
clf = SVC(gamma=0.001, C=100.) clf.fit(Xtrain, ytrain)
```

def decision_function(Xcv, ...): #use appropriate parameters for a data point x_q in Xcv:
#write code to implement $(\sum_{i=1}^{\text{all the support vectors}} (y_i \alpha_i K(x_i, x_q)) + \text{intercept})$, here the values y_i , α_i ,
and *intercept* can be obtained from the trained model return # the decision_function output for all
the data points in the Xcv

fcv = decision_function(Xcv, ...) # based on your requirement you can pass any other parameters

Note: Make sure the values you get as fcv, should be equal to outputs of
clf.decision_function(Xcv)

```
In [3]: # you can write your code here
```

```
data = np.hstack((X, y.reshape(5000,1)))  
data.shape
```

```
Out[3]: (5000, 6)
```

```
In [4]: X_train,X_rem,Y_train,Y_rem = train_test_split(X,y,test_size=0.40,random_state=16)  
X_cv,X_test,Y_cv,Y_test = train_test_split(X_rem,Y_rem,test_size=0.50,random_state=16)
```

```
X_train.shape,X_cv.shape,X_test.shape
```

```
Out[4]: ((3000, 5), (1000, 5), (1000, 5))
```

```
In [5]: model = SVC(gamma = 0.001, C = 100)  
model.fit(X_train,Y_train)
```

```
Out[5]: SVC(C=100, cache_size=200, class_weight=None, coef0=0.0,  
decision_function_shape='ovr', degree=3, gamma=0.001, kernel='rbf',  
max_iter=-1, probability=False, random_state=None, shrinking=True,  
tol=0.001, verbose=False)
```

```
In [6]: f_cv = model.decision_function(X_cv)  
# f_cv
```

```
In [7]: def calculate_rbf(X_i,X_q):  
# k = np.exp(-model.gamma * np.linalg.norm(X_i-X_q))  
k = np.exp(-model.gamma * np.dot(X_i-X_q, X_i-X_q))  
return k
```

```
In [8]: from tqdm import tqdm
```

```
def custom_decision_function(Xcv): #use appropriate parameters  
ycv = np.zeros(Xcv.shape[0]).reshape((Xcv.shape[0],1))  
for i in tqdm(range(Xcv.shape[0])):  
sum = 0  
for j in range(model.support_vectors_.shape[0]):  
kernal = calculate_rbf(model.support_vectors_[j],Xcv[i])  
sum += kernal*model.dual_coef_[0][j]  
ycv[i] = sum + model.intercept_  
return ycv
```

```
100%|| 1000/1000 [00:05<00:00, 186.36it/s]
100%|| 1000/1000 [00:04<00:00, 206.61it/s]
```

```
In [10]: f_cv_custom = f_cv.reshape(1000,1)
```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

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[ 0.00000000e+00]])
```

9F: Implementing Platt Scaling to find $P(Y=1|X)$
Check this PDF

0.2 TASK F

4. Apply SGD algorithm with (f_{cv}, y_{cv}) and find the weight W intercept b
Note: here our data is of one dimensional so we will have a one dimensional weight vector i.e $W.shape (1,)$

Note1: Don't forget to change the values of y_{cv} as mentioned in the above image. you will calculate y_+ , y_- based on data points in train data

Note2: the Sklearn's SGD algorithm doesn't support the real valued outputs, you need to use the code that was done in the 'Logistic Regression with SGD and L2' Assignment after modifying loss function, and use same parameters that used in that assignment. if $Y[i]$ is 1, it will be replaced with y_+ value else it will be replaced with y_- value

5. For a given data point from X_{test} , $P(Y = 1|X) = \frac{1}{1+\exp(-(W*f_{test}+b))}$ where f_{test} = `decision_function(X_{test})`, W and b will be learned as mentioned in the above step

Note: in the above algorithm, the steps 2, 4 might need hyper parameter tuning, To reduce the complexity of the assignment we are excluding the hyperparameter tuning part, but interested students can try that

If any one wants to try other calibration algorithm isotonic regression also please check these tutorials

1. <http://fa.bianp.net/blog/tag/scikit-learn.html#fn:1>
2. https://drive.google.com/open?id=1MzmA7QaP58RDzocB0RBmRiWfl7Co_VJ7
3. https://drive.google.com/open?id=133odBinMOIVb_rh_GQxxsyMRyW-Zts7a
4. https://stat.fandom.com/wiki/Isotonic_regression#Pool_Adjacent_Violators_Algorithm

```
In [11]: N_positive = 0
         N_negative = 0
         for i in range(len(Y_cv)):
             if Y_cv[i] > 0:
                 N_positive +=1
             else:
                 N_negative +=1
         y_positive = (N_positive + 1) / (N_positive + 2)
         y_negative = 1/(N_negative + 2)

         N_positive,N_negative,y_positive,y_negative
```

```
Out[11]: (305, 695, 0.996742671009772, 0.0014347202295552368)
```



```
In [12]: f_cv_custom[0]
```

```
Out[12]: array([-1.80554548])
```

```
In [13]: import math
```

```
def sigmoid(x,w,b):  
    a = np.dot(x,w)+b  
    return 1/(1 + math.exp(-a))
```

```
In [14]: class CustomSGDClassifier:
```

```
    def __init__(self,alpha = 0.0001,N = len(X_train),b = 0,w = np.zeros_like(X_train)  
        self.alpha = alpha  
        self.N = N  
        self.b = b  
        self.w = w  
        self.eta0 = eta0  
        self.ephocs = ephocs  
        self.train_loss = []  
        self.test_loss = []  
        self.result = []
```

```
    def calculateLoss(self,w,b,X,Y):  
        loss = []  
        for i in np.arange(0,len(X)):  
            sig = sigmoid(X[i],w,b)  
            if Y[i] > 0:  
                loss.append(-y_positive*np.log(sig) - (1-y_positive)*np.log(1-sig) + s  
            else:  
                loss.append(-y_negative*np.log(sig) - (1-y_negative)*np.log(1-sig) + s  
        return np.mean(loss)
```

```
    def fit(self,X,Y):  
        initial_loss = self.calculateLoss(w,b,X,Y)  
        # print('Initial Loss:',initial_loss)  
        for ep in range(self.ephocs):  
            for i in range(N):  
                sig = sigmoid(X[i],self.w,self.b)  
                w_new = (1- (self.alpha*self.eta0)/self.N)*self.w + self.eta0*X[i]*(Y  
                b_new = self.b + self.eta0*(Y[i]-sig)  
                self.w = w_new  
                self.b = b_new  
            next_loss = self.calculateLoss(self.w,self.b,X,Y)  
            self.train_loss.append(next_loss)  
            print('-- Epoch: {}, Avg. Train Loss: {}'.format(ep+1,next_loss))  
            if (next_loss < initial_loss) & ((initial_loss-next_loss)<0.0001):  
                break  
        initial_loss = next_loss
```

```

def getProbability(self,X):
    res = []
    for i in range(len(X)):
        prob = 1/(1+math.exp(-(self.w*X[i]+self.b)))
        res.append(prob)
    return res

In [17]: w = np.zeros_like(f_cv_custom[0])
        b = 0
        eta0 = 0.0001
        alpha = 0.0001
        N = len(f_cv_custom)
        # f_test_custom = custom_decision_function(X_test)

        model = CustomSGDClassifier(alpha,N,b,w,eta0,ephocs=30)
        %time model.fit(f_cv_custom,Y_cv)

-- Epoch: 1, Avg. Train Loss: 0.6079155706248737
-- Epoch: 2, Avg. Train Loss: 0.5432836790075528
-- Epoch: 3, Avg. Train Loss: 0.49358708840014864
-- Epoch: 4, Avg. Train Loss: 0.4547003818858166
-- Epoch: 5, Avg. Train Loss: 0.42371468946471313
-- Epoch: 6, Avg. Train Loss: 0.39859299715826124
-- Epoch: 7, Avg. Train Loss: 0.3778994410869025
-- Epoch: 8, Avg. Train Loss: 0.3606085361894483
-- Epoch: 9, Avg. Train Loss: 0.3459761556072111
-- Epoch: 10, Avg. Train Loss: 0.33345327076465753
-- Epoch: 11, Avg. Train Loss: 0.3226281158110312
-- Epoch: 12, Avg. Train Loss: 0.3131870226728602
-- Epoch: 13, Avg. Train Loss: 0.30488754386278194
-- Epoch: 14, Avg. Train Loss: 0.2975397344274488
-- Epoch: 15, Avg. Train Loss: 0.29099291865545984
-- Epoch: 16, Avg. Train Loss: 0.28512619511616644
-- Epoch: 17, Avg. Train Loss: 0.2798415264456194
-- Epoch: 18, Avg. Train Loss: 0.27505864189224627
-- Epoch: 19, Avg. Train Loss: 0.2707112289054954
-- Epoch: 20, Avg. Train Loss: 0.2667440535831429
-- Epoch: 21, Avg. Train Loss: 0.2631107589204572
-- Epoch: 22, Avg. Train Loss: 0.2597721635902968
-- Epoch: 23, Avg. Train Loss: 0.2566949345238134
-- Epoch: 24, Avg. Train Loss: 0.2538505416185785
-- Epoch: 25, Avg. Train Loss: 0.2512144275145971
-- Epoch: 26, Avg. Train Loss: 0.248765342861617
-- Epoch: 27, Avg. Train Loss: 0.24648481005728792
-- Epoch: 28, Avg. Train Loss: 0.24435668754887577
-- Epoch: 29, Avg. Train Loss: 0.2423668134719499
-- Epoch: 30, Avg. Train Loss: 0.2405027123436499

```

Wall time: 1.88 s

```
In [18]: model.w,model.b
```

```
Out[18]: (array([0.98423654]), -0.11499080123800826)
```

```
In [23]: prob_test = model.getProbability(f_test_custom)
         prob_test
```

```
Out[23]: [0.025769892876980352,
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0.06405851825415312,
0.09994338641473573,
0.07492947745587333,
0.6763903707414245,
0.6552342677473902,
0.031403948005559054,
0.5791861511857757,
0.17668830356948265,
0.7555029761206378,
0.07429449336794385,
0.3502396231358732,
0.015303796138847704,
0.5333774848593359,
0.0638187701947497,
0.08168740851304152,
0.9021019834227169,
0.05519775825033845,
0.1236488396362066,
0.8750105402422903,
0.14596182034401456,
0.6777584263814719,
0.7132500857610701,
0.703473955035297,
0.8924699773996331,
0.033190931726194875,
0.018297973356399745,
0.10029944112970829,
0.6645076528820056,
0.129728458923436,
0.7747774264220161,
0.9047066815237239,
0.023180424106962555,
0.06107162928408595,
0.03757267916479918,
0.06855747149561905,
0.11398877952202187,
0.009826080280086746,
0.060913701901350946,
0.7993591648690951,
0.8047786187360438,
0.5664728687080021,
0.046127502156164436,

0.8789188927249879]

```
In [31]: correct = 0
         for i in range(len(Y_test)):
             if (prob_test[i] > 0.5 and Y_test[i]==1) or (prob_test[i] < 0.5 and Y_test[i]==0):
                 correct += 1

         correct, len(Y_test)
```

Out[31]: (932, 1000)