

TP_SVM

August 7, 2017

1 UVF3B403 MS IABDA

1.1 TP sur les SVM

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Dans ce TP nous allons d'abord décortiquer un exemple élémentaire de SVM et puis voir quelques exemples d'utilisation de SVM sous Python. Les packages utilisés seront scikit-learn (et ses sous-packages svm et datasets), numpy et matplotlib.

```
In [1]: # import needed libraries
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import style
from sklearn import svm
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_recall_fscore_support
from sklearn.cross_validation import KFold
```

```
/opt/conda/lib/python3.5/site-packages/sklearn/cross_validation.py:44: DeprecationWarning:
    "This module will be removed in 0.20.", DeprecationWarning)
```

1.2 1 Un SVM élémentaire

Prenons dans le plan euclidien \mathbb{R}^2 les individus (1; 1), (1; 5), (5; 1) et (5; 5), associés aux classes -1; 1; 1; 1.

1.2.1 1 Calculer manuellement le vecteur (a; b) ainsi que la valeur de c de la droite qui sera le séparateur optimal.

```
In [ ]: ## 1. determine support vectors by inspecting data
        ## 2. determine alpha(i): resolve a linear system ( add 1 to every vector a
            # orthogonal vector and the intercept)
        ## 3. determine w= sum(alhpa(i)times s(i))
```

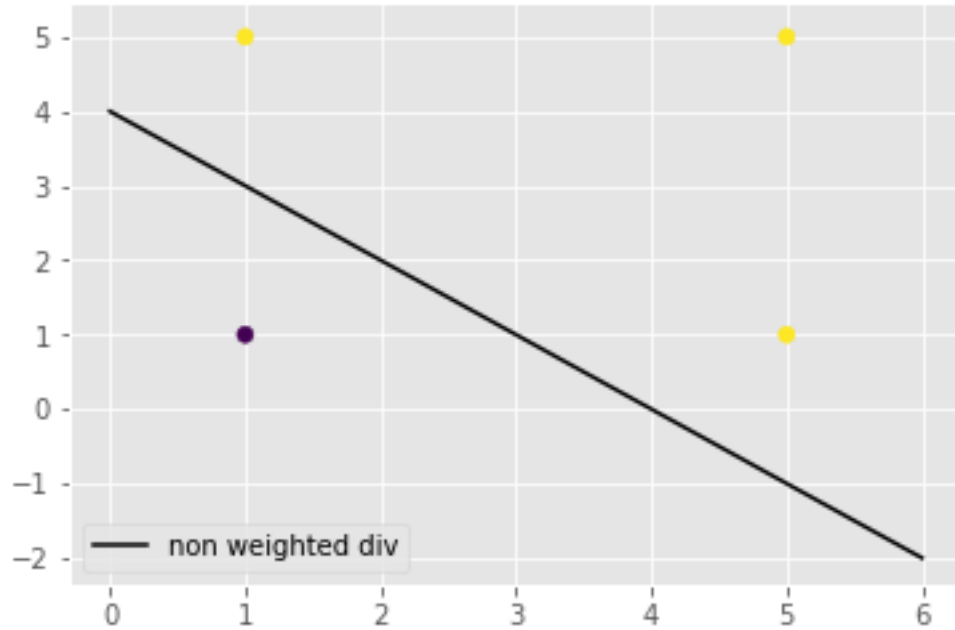
1.2.2 2 Implémenter (bien comprendre le code) :

```
In [2]: style.use("ggplot")
X = np.array([[1, 1], [1, 5], [5, 1], [5, 5]]) # create a np array for our data
y = [-1,1,1,1] # put label for each data point
clf = svm.SVC(kernel='linear') # initialize our classifier, we will use SVM
clf.fit(X, y) # fit the data : X is data( we have 2 features (R*R), y is target

print (clf.support_vectors_) # print the support vectors.By inspection, ok
print (clf.n_support_) #count support vectors for each class. we have one
print( clf.intercept_[0]) # c
w = clf.coef_[0] # the orthogonal vector (a,b)
print(w)
a = -w[0] / w[1] # y=ax+b : a=-w[0] / w[1], b= - clf.intercept_[0] / w[1]
b= - clf.intercept_[0] / w[1]
print( "y=",a, "* x+",b)

xx = np.linspace(0,6)
yy = a * xx + b
plt.plot(xx, yy, 'k-', label="non weighted div")
plt.scatter(X[:, 0], X[:, 1], c = y)
plt.legend()
plt.show()

[[ 1.  1.]
 [ 1.  5.]
 [ 5.  1.]]
[1 2]
-1.99886067708
[ 0.49975586  0.49975586]
y= -1.0 * x+ 3.99967432014
```



1.3 2 Quelques exemples d'applications

On a le choix entre quatre noyaux (option Kernel de SVC) :

Linéaire linear

$$k(x, y) = \langle x, y \rangle$$

polynomial pol

$$k(x, y) = (\gamma \cdot \langle x, y \rangle + r)^d$$

radial rbf

$$k(x, y) = \exp(-\gamma \|x - y\|)$$

sigmoïd sigmoid

$$k(x, y) = \tanh(\gamma \langle x, y \rangle)$$

Les paramètres gamma, d et r s'écrivent gamma, degree et coef0 resp. Le paramètre de coût C (vu en cours) s'écrit cost.

1.3.1 2.1 Iris

Nous allons commencer par les illustres données « iris » de Fischer : la taille en centimètre des pétales et autres parties que je ne saurais nommer de certaines fleurs. Pour chaque individu on a 4 infos numériques et la classe. Les classes sont Iris setosa, Iris versicolor et Iris virginica. On a 150 individus et les classes sont équidistribuées.

step 1: Load data and initialize the classifier

```
In [3]: clf = svm.SVC()
        iris = datasets.load_iris()
        X, y = iris.data, iris.target
```

step 2: split data for train/test using train_test_split function

```
In [4]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,
```

step 3: fit your model

```
In [5]: clf.fit(X_train,y_train)

Out[5]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
            decision_function_shape=None, degree=3, gamma='auto', kernel='rbf',
            max_iter=-1, probability=False, random_state=None, shrinking=True,
            tol=0.001, verbose=False)
```

step 4: predict for X_test using your model that you have just fitted

```
In [6]: y_pred=clf.predict(X_test)
```

step 5: using precision_recall_fscore_support function, under sklearn.metrics package, compute precision, recall and fscore for each class

```
In [7]: precision_recall_fscore_support(y_test, y_pred)

Out[7]: (array([ 1.,  1.,  1.]),
         array([ 1.,  1.,  1.]),
         array([ 1.,  1.,  1.]),
         array([16, 17, 17]))
```

step 6: using KFold in sklearn.cross_validation package, with K=10, compute the average recall and precision for each class

```
In [8]: kf = KFold(150, n_folds=10,shuffle=True)
        Precision=0
        Recall=0
        for train_index, test_index in kf:
            #print("TRAIN:", train_index, "TEST:", test_index)
            X_train, X_test = X[train_index], X[test_index]
            y_train, y_test = y[train_index], y[test_index]

            clf.fit(X_train,y_train)
            y_pred=clf.predict(X_test)
            Precision=np.add(Precision,precision_recall_fscore_support(y_test,y_pre
            Recall=np.add(Recall,precision_recall_fscore_support(y_test,y_pred)[1])
        Precision/10,Recall/10
```

```
/opt/conda/lib/python3.5/site-packages/numpy/lib/arraysetops.py:375: FutureWarning:
mask &= (ar1 != a)
```

```
Out[8]: (array([ 1.          ,  0.98          ,  0.94571429]),
         array([ 1.          ,  0.93238095,  0.9875          ]))
```

step 7: let's put everything together in one function which takes as paramters the kernel and C value.

```
In [25]: def Iris_SVM(kernel_choice,C_value):
        # load data and initialize the classifier with Kernel="kernel" and C=
        # kernels that we can use : 'linear', 'poly', 'rbf', 'sigmoid'
        clf = svm.SVC(C=C_value,kernel=kernel_choice)
        iris = datasets.load_iris()
        X, y = iris.data, iris.target
        '''
        # if you want to test the effect of scaling data before applying SVM:
        scaler = MinMaxScaler()
        df_scaled = pd.DataFrame(scaler.fit_transform(X))
        X_scaled=df_scaled.values
        '''

        # split data into train/test
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.

        # fit and predict
        clf=clf.fit(X_train,y_train)
        y_pred=clf.predict(X_test)

        precision_recall_train_test=precision_recall_fscore_support(y_test, y

        print("Precision, Recall and Fscore for train_test split is :\n",preci

        kf = KFold(150, n_folds=10,shuffle=True)
        Precision=0
        Recall=0
        for train_index, test_index in kf:
            #print("TRAIN:", train_index, "TEST:", test_index)
            X_train_cv, X_test_cv = X[train_index], X[test_index]
            y_train_cv, y_test_cv = y[train_index], y[test_index]

            clf.fit(X_train_cv,y_train_cv)
```

```

y_pred_cv=clf.predict(X_test_cv)
Precision=np.add(Precision,precision_recall_fscore_support(y_test_cv,y_pred_cv))
Recall=np.add(Recall,precision_recall_fscore_support(y_test_cv,y_pred_cv))
print("Precision and Recall for cross validation is : \n", Precision/1)

```

step 8: Call your function for different values of C with the same kernel

```

In [30]: C_values=[1,10]
         for C in C_values:
             print("##### Results for C=",C,":#####\n")
             print(Iris_SVM('rbf',C))

##### Results for C= 1 :#####

Precision, Recall and Fscore for train_test split is :
(array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([1.00000000e+00, 1.00000000e+00, 1.00000000e+00]))
Precision and Recall for cross validation is :
[ 1.          0.975      0.9375] [ 1.          0.94071429  0.975      ]
None
##### Results for C= 10 :#####

Precision, Recall and Fscore for train_test split is :
(array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([1.00000000e+00, 1.00000000e+00, 1.00000000e+00]))
Precision and Recall for cross validation is :
[ 1.          0.96333333  0.90333333] [ 1.          0.92619048  0.96333333]
None

/opt/conda/lib/python3.5/site-packages/numpy/lib/arraysetops.py:375: FutureWarning:
mask &= (ar1 != a)

In [28]: Iris_SVM('rbf',1)

Precision, Recall and Fscore for train_test split is :
(array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([1.00000000e+00, 1.00000000e+00, 1.00000000e+00]))
Precision and Recall for cross validation is :
[ 1.          0.98571429  0.94166667] [ 1.          0.95      0.975]

/opt/conda/lib/python3.5/site-packages/numpy/lib/arraysetops.py:375: FutureWarning:
mask &= (ar1 != a)

```

step 9: Try to use different type of kernels with the same value of C(take C=1)

```

In [23]: kernels=['linear', 'poly', 'rbf', 'sigmoid']
         for kernel in kernels:
             print("##### Results for :", kernel,":#####\n")
             print(Iris_SVM(kernel,1))

```

```
##### Results for : linear #####

Precision, Recall and Fscore for train_test split is :
(array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([1.
Precision and Recall for cross validation is
[ 1.          0.98333333  0.95          ] [ 1.          0.94666667  0.98888889]
None
##### Results for : poly #####

Precision, Recall and Fscore for train_test split is :
(array([ 1.          ,  0.80952381,  1.          ]), array([ 1.          ,  1.          ,
Precision and Recall for cross validation is
[ 1.          0.975  0.955] [ 1.          0.9675          0.98333333]
None
##### Results for : rbf #####

Precision, Recall and Fscore for train_test split is :
(array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([ 1.,  1.,  1.]), array([1.
Precision and Recall for cross validation is
[ 1.          0.98          0.94166667] [ 1.          0.93833333  0.9875          ]
None
##### Results for : sigmoid #####

Precision, Recall and Fscore for train_test split is :
(array([ 0.32,  0.   ,  0.   ]), array([ 1.,  0.,  0.]), array([ 0.48484848,  0.
Precision and Recall for cross validation is
[ 0.08666667  0.06666667  0.04666667] [ 0.4  0.3  0.2]
None

/opt/conda/lib/python3.5/site-packages/numpy/lib/arraysetops.py:375: FutureWarning:
    mask &= (ar1 != a)
/opt/conda/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Unde
    'precision', 'predicted', average, warn_for)
```

1.3.2 2.2 SPAM

Refaire toutes les opérations en utilisant l'ensemble de données « SPAM » du labo Hewlett-Packard (<https://archive.ics.uci.edu/ml/datasets/Spambase>). Les classes sont spam et nonspam. Pour chaque individu on a 57 données numériques et la classe. On a 4 061 individus et les classes sont distribuées de la manière suivante : 39,4% de spam et 60,59% de nonspam. Voir <https://archive.ics.uci.edu/ml/machine-learning-databases/spambase/spambase.DOCUMENTATION> pour la description des données. Faire varier les noyaux et les paramètres et comparer les résultats en fonction de l'importance de la précision et du rappel.

```
In [18]: spambase=pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-data
y1=spambase.pop(57)
```

```
X1=spambase.values
```

```
In [19]: def SpamBase_SVM(kernel_choice,C_value):
    # load data and initialize the classifier with Kernel="kernel" and C=
    # kernels that we can use : 'linear', 'poly', 'rbf', 'sigmoid'
    clf = svm.SVC(C=C_value,kernel=kernel_choice)

    # split data into train/test
    X_train, X_test, y_train, y_test = train_test_split(X1, y1, test_size=

    # fit and predict
    clf=clf.fit(X_train,y_train)
    y_pred=clf.predict(X_test)

    precision_recall_train_test=precision_recall_fscore_support(y_test, y

    print("Precision, Recall and Fscore for train_test split is :\n",preci

    kf = KFold(len(X1), n_folds=10,shuffle=True)
    Precision=0
    Recall=0
    for train_index, test_index in kf:
        #print("TRAIN:", train_index, "TEST:", test_index)
        X_train_cv, X_test_cv = X1[train_index], X1[test_index]
        y_train_cv, y_test_cv = y1[train_index], y1[test_index]

        clf.fit(X_train_cv,y_train_cv)
        y_pred_cv=clf.predict(X_test_cv)
        Precision=np.add(Precision,precision_recall_fscore_support(y_test_
        Recall=np.add(Recall,precision_recall_fscore_support(y_test_cv,y_p
    print("Precision and Recall for cross validation is \n", Precision/10,

In [20]: SpamBase_SVM('linear',1)

In [ ]:
```