Psychoinformatics - Week 9 (Exercises)

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```
import numpy as np
from sklearn import *
from sklearn import model_selection
from matplotlib.pyplot import *
%matplotlib inline
```

1 檢查 machine learning pipeline (8 points)

1.1 請打亂原本的Y觀察正確率是否和chance level (0.33)有差異? 若有, why? (4 points)

```
In [ ]: # 本題在研究打亂X和打亂Y有差別嗎?
       from sklearn import datasets, metrics, neighbors
       iris = datasets.load_iris()
       X=iris.data
       Y=iris.target
       Y2=np.random.permutation(Y)
       clf=neighbors.KNeighborsClassifier(1)
       clf.fit(X,Y2)
       accuracy=np.mean(clf.predict(X)==Y2)
       print('Accuracy of K = 1, X predict random Y',accuracy)
       clf2=neighbors.KNeighborsClassifier(90)
       clf2.fit(X,Y2)
       accuracy2=np.mean(clf3.predict(X)==Y2)
       print('Accuracy of K = 90, X predict random Y',accuracy2)
      Accuracy of K = 90, X predict random Y 0.3733333333333333
```

從本題我們可以發現,由於我們是在predict已經看過的答案(考古題),當K=1時,我們對於任一一個X都可以從KNN的Model裡面找到相對應的考古答案,所以正確率會幾乎全對,而不是像隨機亂猜的0.33,除非我們將K的數值拉的很大(90),它就會參考X最接近的90個X預測的Y,幾乎可以說是亂猜了。打亂X與打亂Y是一樣的結果,除非打亂X的時候我們不是用permutation的方式打亂,而生成新的random_X,像這種情況,兩者就會不一樣,因為此時的random_X已經和原本的X不一樣了。

```
1.2 請用母數或無母數統計檢定以下accuracies中的結果是否和chance level (0.5)有差異? 若
                                                                      有, why? (4 points)
 In [ ]: Y=np.remainder(range(200),2)
                                                                     print(Y) #Y的0和1個數一樣多
                                                           1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 0 \; 1 \; 
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                                                                  101010101010101
 In [ ]: # 跑一百次測試:
                                                                      from sklearn import svm
                                                                      clf=svm.SVC()
                                                                       accuracies=[]
                                                                       for i in range(100):
                                                                             X=np.random.rand(200,2) # X取亂數
                                                                              kf=model_selection.KFold(len(Y),shuffle=True) # Leave-one-out cross-validation
                                                                              sc=model_selection.cross_val_score(clf,X,Y,cv=kf)
                                                                              accuracies.append(sc.mean())
  In [ ]: # Please do your statistical tests here:
                                                                      from scipy.stats import ttest_1samp
                                                                      ttest_1samp(accuracies,0.5)
Out[]: Ttest_1sampResult(statistic=-2.212010537625113, pvalue=0.02926504355653675)
 In [ ]: print(sum(accuracies)/100)
                                                          0.482000000000000015
  In [ ]: #非Leave one out (balanced training dataset)
                                                                      accuracies=[]
                                                                      for i in range(100):
                                                                            X=np.random.rand(200,2) # X取亂數
```

kf=model_selection.KFold(2,shuffle=False) #False, so the training set is always balanced

```
sc=model_selection.cross_val_score(clf,X,Y,cv=kf)
accuracies.append(sc.mean())
# Please do your statistical tests here:
from scipy.stats import ttest_1samp
print('Fold: 2 (balanced training data)')
ttest_1samp(accuracies,0.5)
```

Fold: 2 (balanced training data)

Out[]: Ttest_1sampResult(statistic=-0.484834701057972, pvalue=0.6288646535231612)

Please write your discussion here, if any.

我們可以看到P-value < 0.05 · 也就是說accuracy是顯著的不等於0.5 · 從下方我們算出accuracy的平均約為0.4949 · 會有這樣低於0.5 的accuracy是因為當我們在training的時候使用LOOCV的方式使得training data的Y會呈現 "49個1、50個0" 或是 "50個1、49個0" 兩種 imbalance狀況 · 而由於這些data全是random的 · 所以在兩種狀況中 · 預測結果為Y數量比較多的值將會在training時得到比較低的 error · 但恰好testing data中的Y是數量少的那一個 · 使得Model猜錯的機會增加 · 因而造成正確率低於0.5。

另一方面可以看到,如果我CV使用Fold=2(可使training data balanced),我們可以看到p-value 大於0.05,所以我們不拒絕 accuracy=0.5的假說。

Please submit your notebook in PDF to NTU Cool by next Friday (11/10).