6_Implement_RandomSearchCV_with_k_fold_cross_validation_on_KN

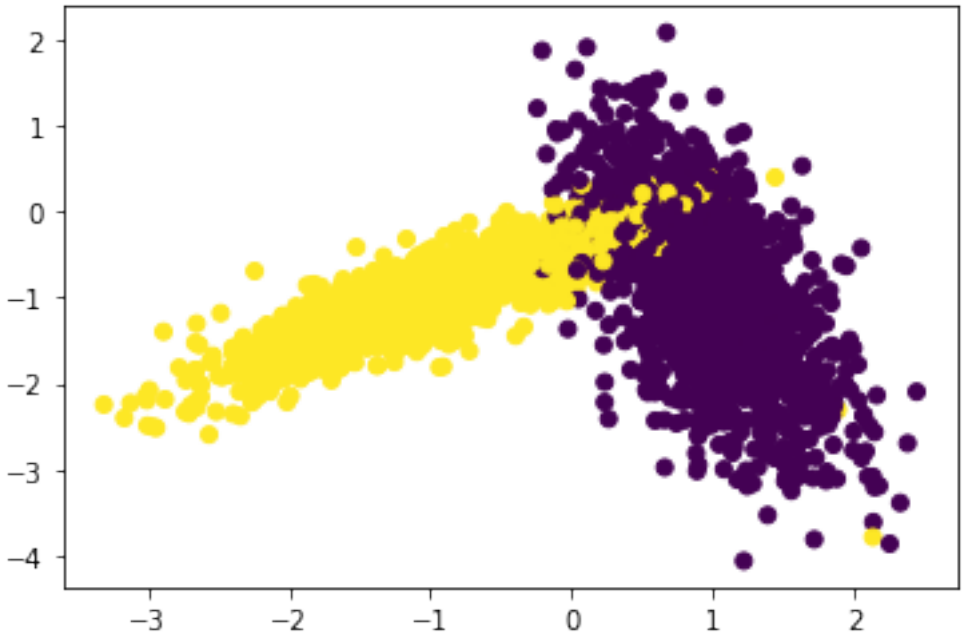
October 21, 2020

[25]:
```
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy
from tqdm import tqdm
import numpy as np
from sklearn.metrics.pairwise import euclidean_distances


x,y = make_classification(n_samples=10000, n_features=2, n_informative=2,␣
 ↪n_redundant= 0, n_clusters_per_class=1, random_state=60)
x_train, x_test, y_train, y_test =␣
 ↪train_test_split(x,y,stratify=y,random_state=42)

# del X_train,X_test
```

[27]:
```
%matplotlib inline
import matplotlib.pyplot as plt
colors = {0:'red', 1:'blue'}
plt.scatter(x_test[:,0], x_test[:,1],c=y_test)
plt.show()
```



[ ]:

1 Implementing Custom RandomSearchCv

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[19]:
```
def get_params(pr):
  '''
  This Function generates the unique random numbers from uniform-distribution.
  '''
  if isinstance(pr,tuple): # checking whether param_range is tuple or not.
    if pr[0]<pr[1] and pr[0]>=0 and pr[1]>0: # conditioning on (low and high) values of tuple to be +ve.
      s = set()
      for i in range(100): # This for-loop generates unique random numbers from uniform-distribution.
        s.add(int(np.random.uniform(low = pr[0],high = pr[1],size=1)))
        if len(s)==10:
          params = list(s)
          break
  return params

def RandomSearchCV(x_train,y_train,classifier, param_range, folds):
  k = get_params(param_range)  # K: Unique Random numbers generated and stored in K.
```

```
 tr = dict() # tr dict is used to store unique k-values and their␣
↪corresponding accuraccy for Training data.
 ts = dict() # ts dict is used to store unique k-values and their␣
↪corresponding accuraccy for Testing data.
 model = classifier
 fold_size = int(len(x_train)/folds)
 for i in tqdm(k): # This for-loop is to compute the accuraccy for different␣
↪k-values and store it in dict {tr and ts}.
   indx = list(range(0,len(x_train)))
   tr_cv_scores,ts_cv_scores = [],[]
   for j in range(folds):# This for-loop is to compute the cv-accuraccy for␣
↪each fold w.r.t unique K.
     cv_indx = list(random.sample(indx,fold_size))
     tr_indx = list(set(list(range(0,len(x_train))))-set(cv_indx))
     for k in cv_indx:
       indx.remove(k)
     #print('cv_indx',cv_indx,'\n','tr_indx',tr_indx)
     x_tr,x_cv = x_train[tr_indx],x_train[cv_indx]
     y_tr,y_cv = y_train[tr_indx],y_train[cv_indx]
     model.n_neighbors = i
     model.fit(x_tr,y_tr)
     tr_cv_scores.append(accuracy_score(y_tr, (model.predict(x_tr))))
     ts_cv_scores.append(accuracy_score(y_cv, (model.predict(x_cv))))
   tr[i] = np.mean(tr_cv_scores)
   ts[i] = np.mean(ts_cv_scores)
 #print(tr,'\n',ts)
 return tr,ts
```

[118]:

[20]:
```
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy
from tqdm import tqdm
import numpy as np
from sklearn.metrics.pairwise import euclidean_distances

from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt
import random
import warnings
warnings.filterwarnings("ignore")
```

```
x,y = make_classification(n_samples=10000, n_features=2, n_informative=2,␣
 ↪n_redundant= 0, n_clusters_per_class=1, random_state=60)
x_train, x_test, y_train, y_test =␣
 ↪train_test_split(x,y,stratify=y,random_state=42)

# del X_train,X_test
```

[21]:
```
classifier = KNeighborsClassifier()
param_range = (1,32)
folds = 10
tr_score,ts_score = RandomSearchCV(x_train,y_train,classifier, param_range,␣
 ↪folds)
plt.grid()
plt.plot(list(tr_score.keys()),list(tr_score.values()),'-o',label =␣
 ↪'Train-Curve')
plt.plot(list(ts_score.keys()),list(ts_score.values()),'-o',label =␣
 ↪'Test-Curve')
plt.title('hyper-parameter vs accuracy plot')
plt.legend()
plt.show()
```

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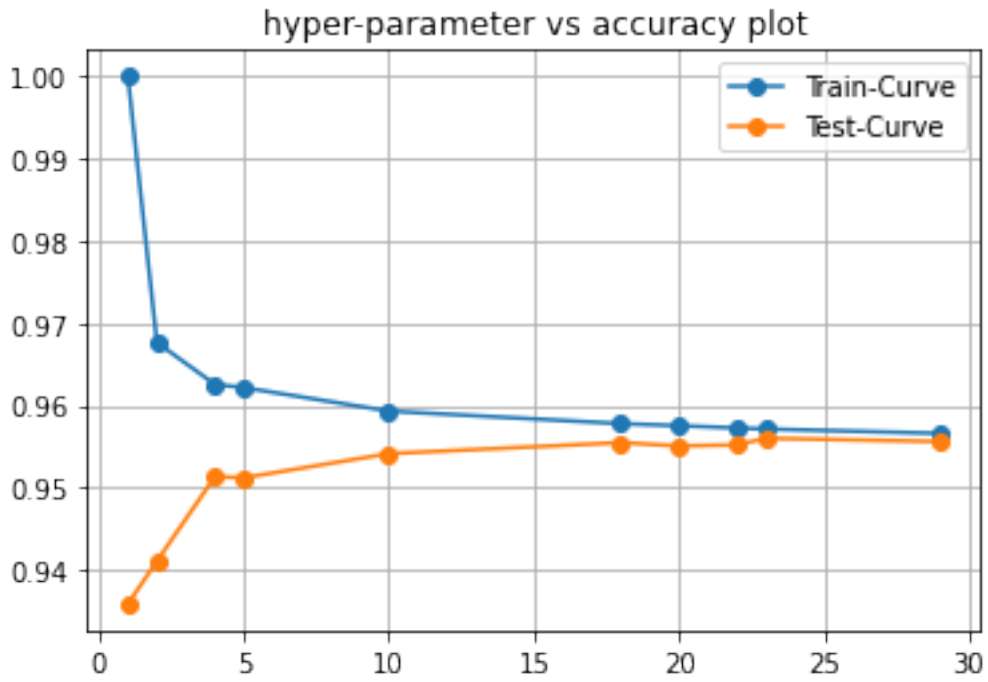
```



[23]:
```
# understanding this code line by line is not that importent
def plot_decision_boundary(X1, X2, y, clf):
```

```
        # Create color maps
    cmap_light = ListedColormap(['#FFAAAA', '#AAFFAA', '#AAAAFF'])
    cmap_bold = ListedColormap(['#FF0000', '#00FF00', '#0000FF'])

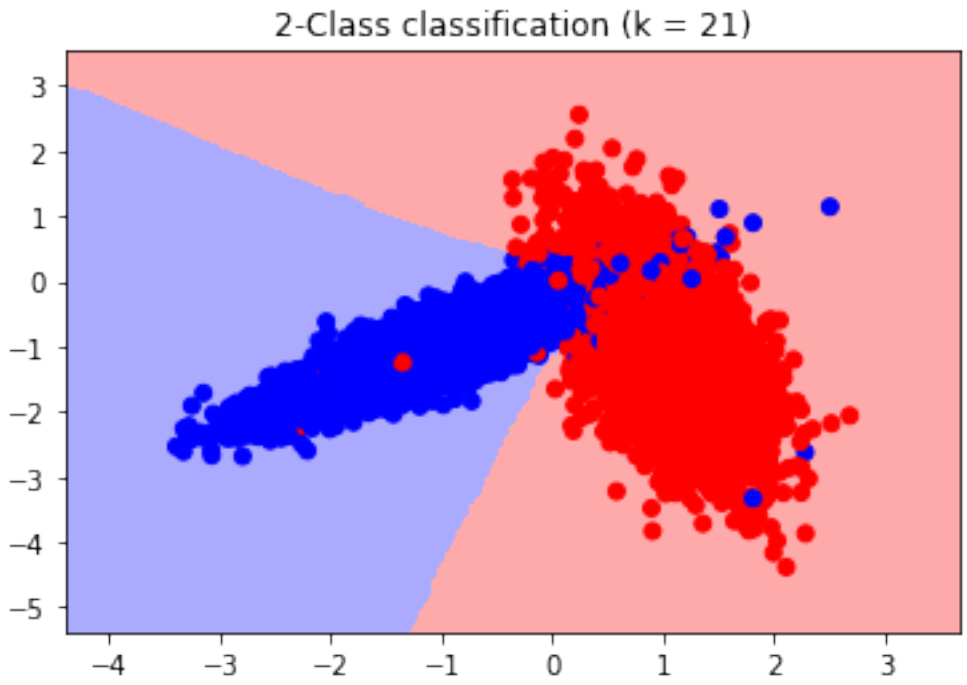
    x_min, x_max = X1.min() - 1, X1.max() + 1
    y_min, y_max = X2.min() - 1, X2.max() + 1

    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02), np.arange(y_min, y_max,␣
↪0.02))
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    plt.figure()
    plt.pcolormesh(xx, yy, Z, cmap=cmap_light)
    # Plot also the training points
    plt.scatter(X1, X2, c=y, cmap=cmap_bold)

    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())
    plt.title("2-Class classification (k = %i)" % (clf.n_neighbors))
    plt.show()
```

[24]:
```
from matplotlib.colors import ListedColormap
neigh = KNeighborsClassifier(n_neighbors = 21)
neigh.fit(x_train, y_train)
plot_decision_boundary(x_train[:, 0], x_train[:, 1], y_train, neigh)
```



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