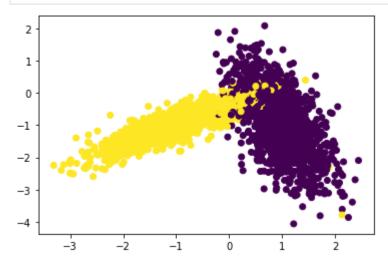
```
In [6]: from sklearn.datasets import make_classification
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    import numpy
    from tqdm import tqdm
    import numpy as np
    from sklearn.metrics.pairwise import euclidean_distances

x,y = make_classification(n_samples=10000, n_features=2, n_informative=2, n_redundant=
    X_train, X_test, y_train, y_test = train_test_split(x,y,stratify=y,random_state=42)

# del X_train,X_test
```

Implementing Custom RandomSearchCV

```
def RandomSearchCV(x_train,y_train,classifier, param_range, folds):
    # x_train: its numpy array of shape, (n,d)
    # y_train: its numpy array of shape, (n,) or (n,1)
    # classifier: its typically KNeighborsClassifier()
    # param_range: its a tuple like (a,b) a < b
    # folds: an integer, represents number of folds we need to devide the data and test our model</pre>
```

```
#1.generate 10 unique values(uniform random distribution) in the
given range "param_range" and store them as "params"
    # ex: if param_range = (1, 50), we need to generate 10 random numbers
in range 1 to 50
    #2.devide numbers ranging from 0 to len(X_train) into groups= folds
    # ex: folds=3, and len(x_train)=100, we can devide numbers from 0 to
100 into 3 groups
```

```
group 1: 0-33, group 2:34-66, group 3: 67-100
   #3.for each hyperparameter that we generated in step 1:
       # and using the above groups we have created in step 2 you will
do cross-validation as follows
        # first we will keep group 1+group 2 i.e. 0-66 as train data and
group 3: 67-100 as test data, and find train and
          test accuracies
       # second we will keep group 1+group 3 i.e. 0-33, 67-100 as train
data and group 2: 34-66 as test data, and find
          train and test accuracies
       # third we will keep group 2+group 3 i.e. 34-100 as train data
and group 1: 0-33 as test data, and find train and
          test accuracies
       # based on the 'folds' value we will do the same procedure
       # find the mean of train accuracies of above 3 steps and store in
a list "train scores"
       # find the mean of test accuracies of above 3 steps and store in
a list "test scores"
    #4. return both "train scores" and "test scores"
#5. call function RandomSearchCV(x_train,y_train,classifier, param_range,
folds) and store the returned values into "train_score", and "cv_scores"
#6. plot hyper-parameter vs accuracy plot as shown in reference notebook
and choose the best hyperparameter
#7. plot the decision boundaries for the model initialized with the best
hyperparameter, as shown in the last cell of reference notebook
```

from sklearn.metrics import accuracy score In [35]: def get test indices set(x train,block size,j): if j==1: test index = [*range(int(block size*(j-1) *len(x train)) , int ((block size* return test index def RandomSearchCV(x_train,y_train,classifier, params, folds): trainscores = [] testscores = [] par_range = params['n_neighbors'] #range of parameters K rand_params = [] for i in range (10): rand params.append(random.randrange(par range[0] , par range[1]+1)) #qeneratin rand_params = sorted(rand_params) #sorted list of random parameters for k in tqdm(rand_params):

```
trainscores_folds = []
    testscores folds = []
    block size = round(float(100/(folds*100)),2)
                                                   #block size , length of each
    for j in range(0, folds):
        test_indices = get_test_indices_set(x_train,block_size,j+1)
                                                                      #getting te
        train indices = list(set(list(range(1, len(x train)))) - set(test indices))
        # selecting the data points based on the train_indices and test_indices
        X train = x train[train indices] # train set x
        Y train = y train[train indices] # train set y
        X_test = x_train[test_indices] #CV
        Y_test = y_train[test_indices] #CV
        classifier.n neighbors = k
                                            #hyperparameter k
        classifier.fit(X_train,Y_train)
                                             #fit to model
        Y_predicted = classifier.predict(X_test) #predict CV
        testscores_folds.append(accuracy_score(Y_test, Y_predicted))
                                                                      #accuracy s
        Y_predicted = classifier.predict(X_train) #predict train
        trainscores folds.append(accuracy score(Y train, Y predicted)) #accuracy s
    trainscores.append(np.mean(np.array(trainscores folds))) #average train set sco
    testscores.append(np.mean(np.array(testscores_folds))) #average CV set scores
return trainscores, testscores, rand params
```

```
from sklearn.metrics import accuracy score
In [37]:
          from sklearn.neighbors import KNeighborsClassifier
          import matplotlib.pyplot as plt
          import random
          import warnings
          warnings.filterwarnings("ignore")
          neigh = KNeighborsClassifier()
          params_range = {'n_neighbors':(1,50)}
          folds = 3
          trainscores, testscores, rand params = RandomSearchCV(X train, y train, neigh, params ran
          print(rand params)
          plt.plot(rand_params, trainscores, label='train cruve')
          plt.plot(rand_params, testscores, label='test cruve')
          plt.title('Hyper-parameter VS accuracy plot')
          plt.legend()
```

```
plt.show()

#K=45 has the highest test accuracy and distance to the train curve is shortest
```

```
100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%|
```

```
0.965 - Hyper-parameter VS accuracy plot

train cruve test cruve

0.955 - 0.950 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.945 - 0.94
```

```
In [38]:
          # 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()
```

