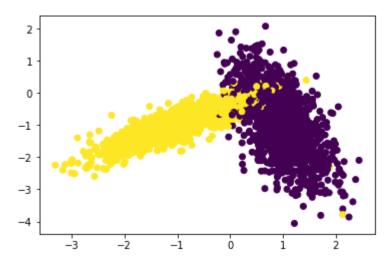
```
In [96]: from sklearn.datasets import make_classification
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    import numpy
    from tqdm import tqdm
    import numpy as np
    from sklearn.metrics.pairwise import euclidean_distances

x,y = make_classification(n_samples=10000, n_features=2, n_informative=2, n_redundant= 0, n_clusters_per_class=1
    X_train, X_test, y_train, y_test = train_test_split(x,y,stratify=y,random_state=42)

# del X_train,X_test
```

In [97]: %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()



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
    #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, a
nd 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, a
nd 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
```

#6. plot hyper-parameter vs accuracy plot as shown in reference notebook and choose the best hyperparame localhost:8888/notebooks/Untitled Folder/Assignment 4 Instructions.ipynb#

values into "train score", and "cv scores"

ter

#7. plot the decision boundaries for the model initialized with the best hyperparameter, as shown in the last cell of reference notebook

```
In [98]:
```

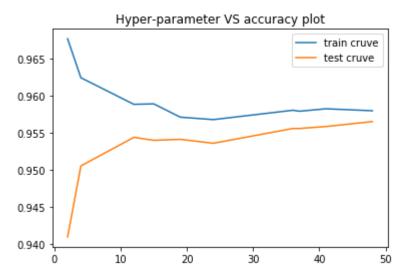
```
def RandomSearchCV(x train,y train,classifier, param range, folds):
    params=set()
   trainscores = []
    cvscores = []
   while len(params)!=10:
        params.add(int(random.uniform(param range[0],param range[1])))
   params=list(params) #Generating 10 random values of K from the range configurable range(1,50)
    params.sort() #Sorting the values of k in asc order for grapph to be plotted neatly
   #https://stackoverflow.com/questions/58756377/how-does-the-numpy-function-array-split-work-mathematically
   #Calculating the size of sections by dividing the data set(x train) by value of folds
   quotient, remainder = divmod(len(x train), folds)
   section sizes = (remainder * [quotient+1] +(folds- remainder) * [quotient])
   for k in params:
        trainscores folds = []
        cvscores folds = []
        u=0
        t=0
       for i in range(0, folds):
           t+=section_sizes[i]
            cv indices=list(x for x in range(u,t)) #calculating the CV indices
           train indices = list(set(list(range(0, len(x train)))) - set(cv indices)) #calculating the train ind
            u+=section sizes[i]
            temp tr x=x train[train indices]
            temp tr y=y train[train indices]
            temp cv x=x train[cv indices]
            temp cv y=y train[cv indices]
            classifier.n neighbors = k
            classifier.fit(temp tr x,temp tr y)
           Y predicted = classifier.predict(temp cv x) #CV prediction
            cvscores folds.append(accuracy score(temp cv y, Y predicted))
```

```
Y_predicted = classifier.predict(temp_tr_x) #Train prediction
    trainscores_folds.append(accuracy_score(temp_tr_y, Y_predicted))

trainscores.append(np.mean(np.array(trainscores_folds)))
  cvscores.append(np.mean(np.array(cvscores_folds)))
return trainscores,cvscores,params
```

```
In [111]: from sklearn.metrics import accuracy score
           from sklearn.neighbors import KNeighborsClassifier
           import matplotlib.pyplot as plt
           import random
           import warnings
           warnings.filterwarnings("ignore")
           import numpy as np
           classifier = KNeighborsClassifier()
           folds=int(input("Enter the number of folds you want: "))
           param_range=(1,50)
          trainscores, testscores, params=RandomSearchCV(X_train, y_train, classifier, param_range, folds)
           #print(trainscores)
           #print(testscores)
           #print(len(params))
           plt.plot(params,trainscores, label='train cruve')
           plt.plot(params, testscores, label='test cruve')
           plt.title('Hyper-parameter VS accuracy plot')
           plt.legend()
           plt.show()
```

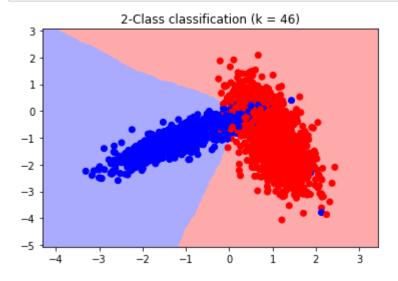
Enter the number of folds you want: 3



From the above graph we observe that the test accuracy and train accuracy are closest at K=46. Thus taking the value of K=46 for X_test

```
In [101]: 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()
```

```
In [110]: from matplotlib.colors import ListedColormap
    neigh = KNeighborsClassifier(n_neighbors = 46)
    neigh.fit(X_train, y_train)
    plot_decision_boundary(X_test[:, 0], X_test[:, 1], y_test, neigh)
```



In []: