```
In [2]: !pip install tqdm
        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
        WARNING: pip is being invoked by an old script wrapper. This will fail in a future version of
        Please see https://github.com/pypa/pip/issues/5599 for advice on fixing the underlying issue.
        To avoid this problem you can invoke Python with '-m pip' instead of running pip directly.
        Collecting tqdm
          Downloading tqdm-4.45.0-py2.py3-none-any.whl (60 kB)
                                             | 60 kB 2.5 MB/s eta 0:00:011
        Installing collected packages: tqdm
        Successfully installed tqdm-4.45.0
In [3]: %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()
          0
         -1
         -3
               -3
                     -2
        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</pre>
               # folds: an integer, represents number of folds we need to devide the data and tes
            t our model
               #1.generate 10 unique values(uniform random distribution) in the given range "para
            m_range" and store them as "params"
               # ex: if param_range = (1, 50), we need to generate 10 random numbers in range 1 t
               #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 gr
            oups
                  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-valid
           ation as follows
                    # first we will keep group 1+group 2 i.e. 0-66 as train data and group 3: 67-1
            00 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 grou
            p 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 "trai
           n_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 s
            tore the returned values into "train_score", and "cv_scores"
            #6. plot hyper-parameter vs accuracy plot as shown in reference notebook and choose th
            e best hyperparameter
            #7. plot the decision boundaries for the model initialized with the best hyperparamete
            r, as shown in the last cell of reference notebook
        Generating 10 number numbers
In [4]: def generate_10_random_numbers(a):
          if a[0] < a[1]:
            r = np.random.uniform(a[0],a[1],10)
            r = list(r.astype(int))
            r.sort()
            if len(r) == len(set(r)):
              return r
              r = generate_10_random_numbers(a)
          else:
            print('Error: param_range: its a tuple like (a,b) a < b ')</pre>
        divide numbers ranging from 0 to len(X_train) into 3 folds
In [5]: def divide_training_dataset_to_k_folds(x_train,y_train,folds):
            temp = len(x_train)/folds
            x_train = x_train.tolist()
            y_train = y_train.tolist()
            group = []
            label = []
            end = 0.0
            while end < len(x_train):</pre>
              group.append(x_train[int(end):int(end + temp)])
              label.append(y_train[int(end):int(end + temp)])
              end += temp
            return group,label
        defining RandomSearch Function
In [6]: from sklearn.metrics import accuracy_score
        def RandomSearchCV(x_train, y_train, classifier, param_range, folds):
            #Generate 10 unique values(uniform random distribution) in the given range "param range"
        and store them as "params"
            params = generate_10_random_numbers(param_range)
            if params == 0:
              exit()
            # divide numbers ranging from 0 to len(X_train) into groups= folds
            temp = len(x_train)/folds
            temp = int(temp)
            groups, labels = divide_training_dataset_to_k_folds(x_train,y_train,folds)
            train_scores = []
            test_scores = []
            for k in tqdm(params):
              for i in range(folds):
                trainscores_folds = []
                testscores_folds = []
                X_train = [groups[iter] for iter in range(folds) if iter != i]
                X_train = [j for sublist in X_train for j in sublist]
                Y_train = [labels[iter] for iter in range(folds) if iter != i]
                Y_train = [j for sublist in Y_train for j in sublist]
                X_test = groups[i]
                Y_test = labels[i]
                classifier.n\_neighbors = k
                #print(np.asarray(Y_train))
                classifier.fit(X_train,Y_train)
                Y_predicted = classifier.predict(X_test)
                testscores_folds.append(accuracy_score(Y_test, Y_predicted))
                Y_predicted = classifier.predict(X_train)
                trainscores_folds.append(accuracy_score(Y_train, Y_predicted))
              train_scores.append(np.mean(np.array(trainscores_folds)))
              test_scores.append(np.mean(np.array(testscores_folds)))
            #4. return both "train_scores" and "test_scores"
            return train_scores, test_scores, params
        call function RandomSearchCV
In [7]: ## call function RandomSearchCV(x_train, y_train, classifier, param_range, folds) and store th
        e returned values into "train_score", and "cv_scores"
        from sklearn.metrics import accuracy_score
        from sklearn.neighbors import KNeighborsClassifier
        import matplotlib.pyplot as plt
        import random
        import warnings
        warnings.filterwarnings("ignore")
        classifier = KNeighborsClassifier()
```

```
plt.show()
                           Hyper-parameter VS accuracy plot
            1.00
                                                             train cruve
                                                             test cruve
            0.99
            0.98
            0.97
            0.96
            0.95
            0.94
            0.93
                            10
                                       20
                                                  30
                                                             40
In [9]: params
```

In [11]: # 7. plot the decision boundaries for the model initialized with the best hyperparameter, as

Plotting the decision boundaries

shown in the last cell of reference notebook

Out[9]: [1, 2, 3, 6, 7, 11, 18, 25, 46, 47]

```
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 [12]: | from matplotlib.colors import ListedColormap
         neigh = KNeighborsClassifier(n_neighbors = 18)
         neigh.fit(X_train, y_train)
         plot_decision_boundary(X_train[:, 0], X_train[:, 1], y_train, neigh)
```

```
3 - 2 - 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
```

```
2
1
0
-1
-2
-3
-4
-5
-4 -3 -2 -1 0 1 2 3
```

2-Class classification (k = 18)

## Reference

Mail of randomsearch provided by appliedai

GridSearchCV coding in Assignment 4 reference