### Importing the necessary libraries

```
In [39]: 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
    import random
    from sklearn.metrics import accuracy_score
    from random import seed
```

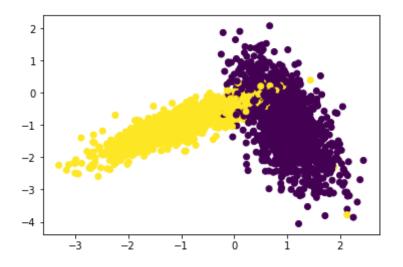
### creating the artifical data

```
In [40]: x,y = make_classification(n_samples=10000, n_features=2, n_informative=
2, n_redundant= 0, n_clusters_per_class=1, random_state=60)
```

#### Dividing the data into train and test

```
In [41]: X_train, X_test, y_train, y_test = train_test_split(x,y,stratify=y,rand
om_state=42)
```

```
In [42]: %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()
```



### Implementation of randomsearchCV function

```
In [45]: def RandomSearchCV(x_train,y_train,classifier, param_range, folds):
             trainscores = []
             testscores = []
             global params
             params=[]
             seed(7)
             params= random.sample(range(param range[0],param range[1]), 10) # c
         reating random set of unique numbers
             params.sort() # sorting parameters
             print(params)
             length = int(len(x train)/folds)
             foldsX = []
             foldsY = []
             for i in range(folds-1):
                 foldsX += [x train[i*length:(i+1)*length]]
                 foldsY += [y train[i*length:(i+1)*length]]
                                                                  #block of sta
         tement used for creating folds
             foldsX += [x_train[(folds-1)*length:len(x train)]]
             foldsY += [y train[(folds-1)*length:len(y train)]]
             for k in tqdm(params):
```

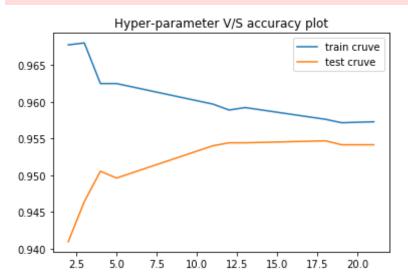
```
trainscores folds = []
                 testscores \overline{folds} = []
                 for j in range(0, folds):
                     X \text{ test} = foldsX[i]
                     Y test = foldsY[i]
                     G=np.delete(foldsX,j,0) #removing cross validation dat
         a
                     V=np.delete(foldsY, j, 0)
                     X train = np.concatenate(G)
                     Y train = np.concatenate(V) # data used for training
                      classifier.n neighbors = k
                      classifier.fit(X_train,Y_train)
                     Y predicted = classifier.predict(X test)
                     testscores folds.append(accuracy score(Y test, Y predicted
         )) # calculating accuracy score for each fold
                     Y predicted = classifier.predict(X train)
                     trainscores folds.append(accuracy score(Y train, Y predicte
         d))
                 trainscores.append(np.mean(np.array(trainscores folds)))
                 testscores.append(np.mean(np.array(testscores folds))) # calcul
         ating the accuracy score for each k
             return trainscores, testscores
In [46]: from sklearn.metrics import accuracy score
         from sklearn.neighbors import KNeighborsClassifier
         import matplotlib.pyplot as plt
         import random
         import warnings
         warnings.filterwarnings("ignore")
         neigh = KNeighborsClassifier()
         param range=(1,30)
         folds = 3
         trainscores, testscores = RandomSearchCV(X train, y train, neigh, param ra
         nge, folds) # calling the function
```

plt.plot(params, trainscores, label='train cruve')

```
plt.plot(params, testscores, label='test cruve')
plt.title('Hyper-parameter V/S accuracy plot')
plt.legend()
plt.show()
print(params)
```

[2, 3, 4, 5, 11, 12, 13, 18, 19, 21]

# 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%| 100%|



[2, 3, 4, 5, 11, 12, 13, 18, 19, 21]

• from the plot we can see that k=18 is the best hyper parameter

```
, 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)
  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()
```

## Drawing decision boundry for optimal k

```
In [48]: 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)
```

