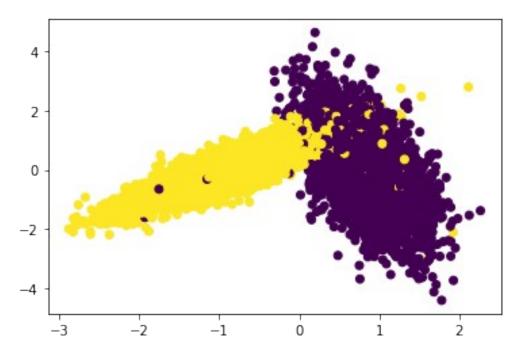
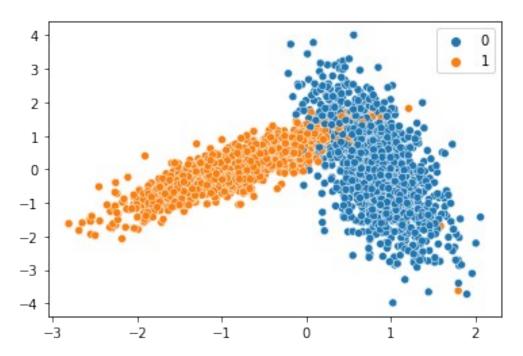
```
from sklearn.datasets import make classification
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
import numpy as np
import collections
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy score
import random
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,test size)
=0.25, stratify=y, random_state=42,)
standard=StandardScaler()
X train=standard.fit transform(X train)
X test=standard.transform(X test)
X_train.shape,X_test.shape
((7500, 2), (2500, 2))
print("Number of classes {}".format(np.unique(y_train)))
Number of classes [0 1]
for k,v in collections.Counter(y train).items():
  print("class {1} has {0} data points".format(v,k))
class 0 has 3740 data points
class 1 has 3760 data points
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
plt.scatter(X train[:,0], X train[:,1],c=y train)
plt.show()
```



sns.scatterplot(X\_test[:,0], X\_test[:,1],hue=y\_test)
plt.show()

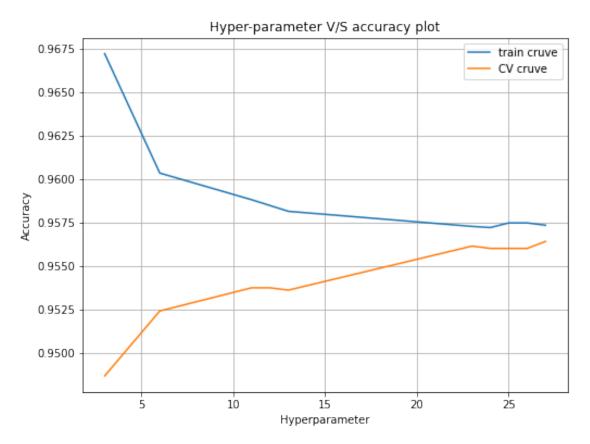
/usr/local/lib/python3.7/dist-packages/seaborn/\_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

FutureWarning



```
Implementing Custom RandomSearchCV
def params gen(t):
  A=random.sample(range(t[0],t[1]),10)
  #print(sorted(A))
  return sorted(A)
def RandomSearchCV(X,Y,knn, param_range, folds):
  params=params gen(param range)
  CV = [1]
  train=[]
  for p in params:
   cv accuracies=[]
   train accuracies=[]
    for f in range(0, folds):
      start idx=round(len(X)/folds)*(f)
      end_idx=round((len(X)/folds)*(f+1))-1
      cv indices=set(np.arange(start idx,end idx+1))
      train indices=list(set(np.arange(0,len(X)))-cv indices)
      cv indices=list(cv indices)
      #-----
      knn.n neighbors=p
      knn.fit(X[train indices],Y[train indices])
      #-----predicting train points-----
     y_train_pred=knn.predict(X[train_indices])
      #-----predicting test points-----
     y cv pred=knn.predict(X[cv indices])
      #-----AUC scores----
      cv_accuracies.append(accuracy_score(Y[cv indices],y cv pred))
train accuracies.append(accuracy score(Y[train indices],y train pred))
   CV.append(np.mean(cv accuracies))
    train.append(np.mean(train accuracies))
  return train,CV,params
cll=KNeighborsClassifier()
folds=3
param range=(1,30)
train auc,cv score,params=RandomSearchCV(X train,y train,cll,
param range, folds)
plt.figure(figsize=(8,6))
plt.plot(params,train auc, label='train cruve')
plt.plot(params,cv score, label='CV cruve')
plt.title('Hyper-parameter V/S accuracy plot')
plt.legend()
plt.xlabel("Hyperparameter")
plt.ylabel("Accuracy")
```

```
plt.grid()
plt.show()
#print(params)
```



```
#params,cv score
cll.n neighbors=23
cll.fit(X_train,y_train)
y_pred=cll.predict(X_test)
test_AUC=accuracy_score(y_test,y_pred)
print("Accuracy on test data "+str(test AUC*100))
Auccuracy on test data 96.8
#Compairing with sklearn's implementation
from sklearn.model_selection import RandomizedSearchCV
p= {'n neighbors':[3, 6, 11, 12, 13, 23, 24, 25, 26, 27]}
obj=KNeighborsClassifier()
R_CV=RandomizedSearchCV(obj, param_distributions=p,cv=3)
R_CV.fit(X_train,y_train)
RandomizedSearchCV(cv=3, estimator=KNeighborsClassifier(),
                   param distributions={'n neighbors': [3, 6, 11, 12,
13, 23,
```

```
24, 25, 26, 27]})

R_CV.best_estimator_, R_CV.best_params_, R_CV.best_score_

(KNeighborsClassifier(n_neighbors=23), {'n_neighbors': 23}, 0.95613333333333)

R_CV.best_index_

5

# Our custom implementation of Random Search CV is matching with sklearn's implementation.
params[5], cv_score[5]
```

(23, 0.9561333333333333)