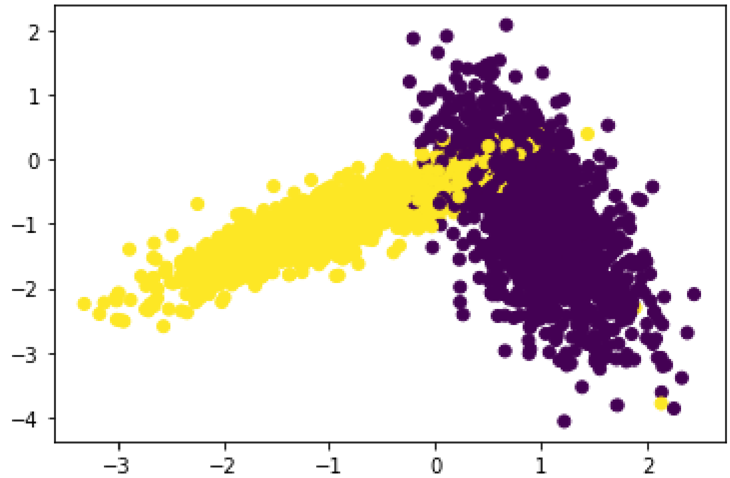
In [2]:

```
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_redundan
X_train, X_test, y_train, y_test = train_test_split(x,y,stratify=y,random_state=42)

# del X_train,X_test
```

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()
```



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, 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
```

In [11]:

```python
from sklearn.metrics import accuracy_score
import random
from tqdm import tqdm

def random_params_range_1_to_len(params_range):
    sort_values = random.sample(range(1, params_range),10)
    sort_values.sort()
    return sort_values

def RandomSerachCV(x_train, y_train, classifier, params, folds):
    trainscores = []
    testscores  = []

    #Randomly selecting numbers from params_range
    params_list= random_params_range_1_to_len(params_range)
    #printing the random paramter values
    print(params_list)

    params = {'n_neighbors': params_list}

    for k in tqdm(params['n_neighbors']):

        trainscores_folds = []
        testscores_folds  = []

        for i in range(0, folds):
            #finding length of group
```

```
            group_interval = int(len(x_train)/(folds))

            test_indices = list(range((group_interval*i), (group_interval*(i+1))))
            train_indices = list(set(list(range(0, len(x_train)))) - set(test_indice

            # selecting the data points based on the train_indices and test_indices
            X_train = x_train[train_indices]
            Y_train = y_train[train_indices]
            X_test  = x_train[test_indices]
            Y_test  = y_train[test_indices]

            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))

            Y_predicted = classifier.predict(X_train)
            trainscores_folds.append(accuracy_score(Y_train, Y_predicted))
        trainscores.append(np.mean(np.array(trainscores_folds)))
        testscores.append(np.mean(np.array(testscores_folds)))
    return trainscores,testscores,params
```

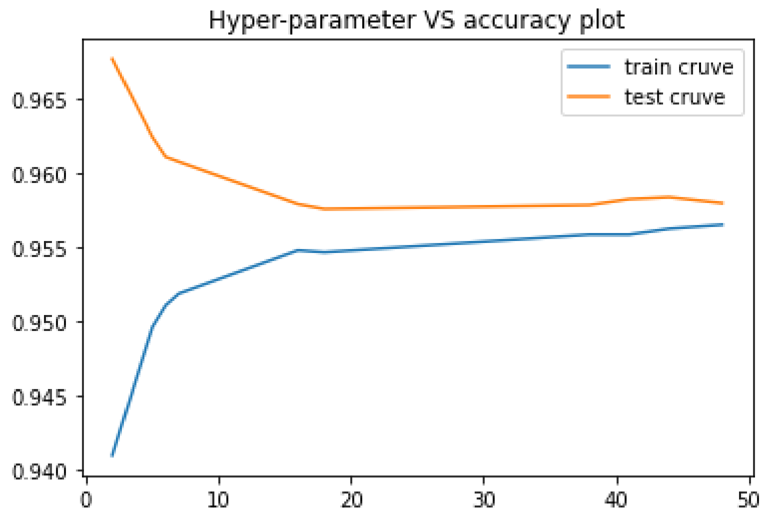
In [12]:

```
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()
params_range = 50
folds = 3

testscores, trainscores, params = RandomSerachCV(X_train, y_train, neigh, params_ran

print(params)
print(trainscores)
print(testscores)

plt.plot(params['n_neighbors'],trainscores, label='train cruve')
plt.plot(params['n_neighbors'],testscores, label='test cruve')
plt.title('Hyper-parameter VS accuracy plot')
plt.legend()
```

```
[2, 5, 6, 7, 16, 18, 38, 41, 44, 48]
100%|██████████████████████████████████████████| 10/10 [00:09<00:00,  1.04it/s]
{'n_neighbors': [2, 5, 6, 7, 16, 18, 38, 41, 44, 48]}
[0.9409333333333333, 0.9495999999999999, 0.9510666666666667, 0.9518666666666666, 0.9
548, 0.9546666666666667, 0.9558666666666666, 0.9558666666666666, 0.9562666666666667,
0.9565333333333333]
[0.9677333333333333, 0.9624666666666667, 0.9611333333333333, 0.9608, 0.9579333333333
334, 0.9575999999999999, 0.9578666666666665, 0.9582666666666667, 0.9584, 0.957999999
9999999]
```

Out[12]:

```
<matplotlib.legend.Legend at 0x26b1784ab50>
```

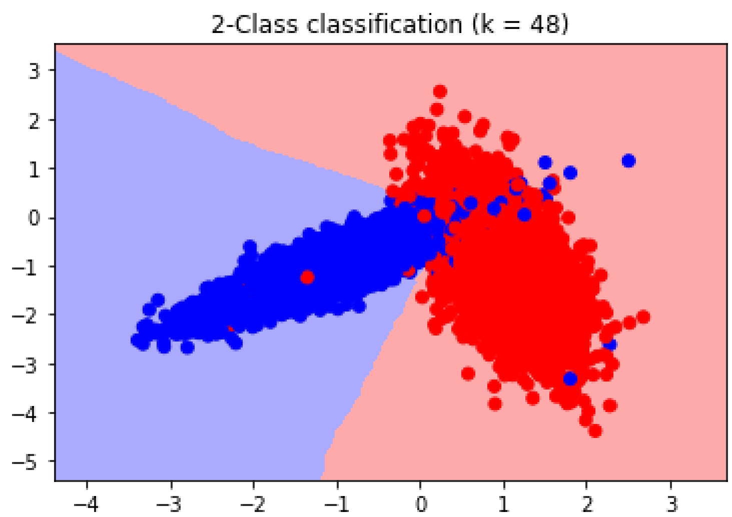


In [13]:

```
# taking it from reference
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 [17]:

```
from matplotlib.colors import ListedColormap
neigh = KNeighborsClassifier(n_neighbors = 48)
neigh.fit(X_train, y_train)
plot_decision_boundary(X_train[:, 0], X_train[:, 1], y_train, neigh)
```



Conclusion-

- Choosing optimum K hyperparameter value as **48** because it has the highest CV accuracy and the gap between train and cv curves is minimun at k = 48.