sheet09_C4M2

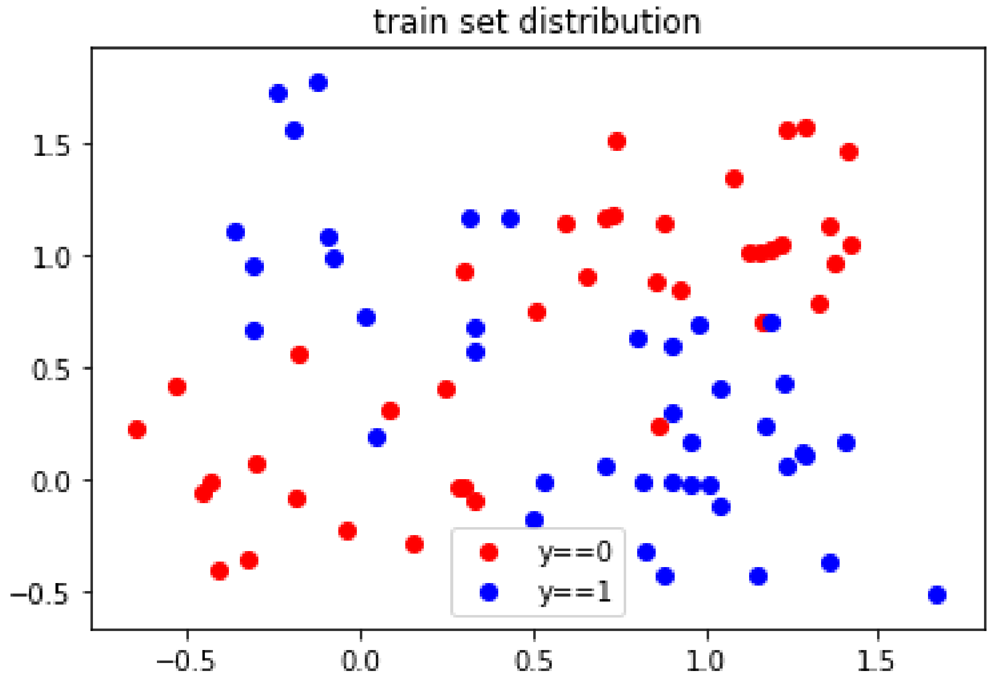
January 17, 2018

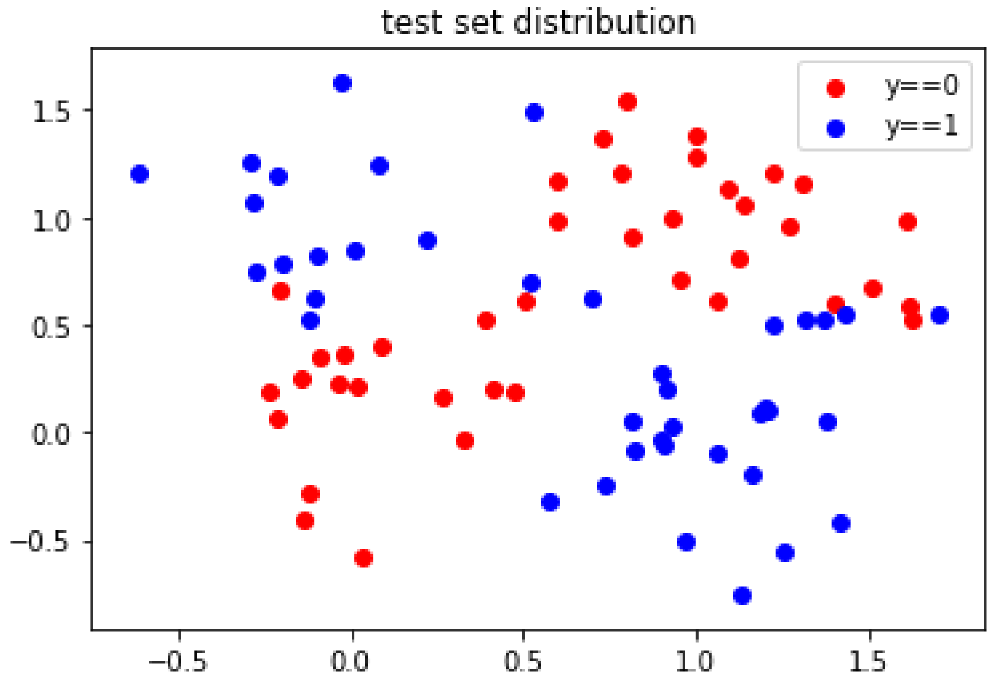
1 H9.2 C-SVM with standard parameters

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.model_selection import KFold
%matplotlib inline
```

In [2]:
```
def SampleMixtureNormal2D(m1, s1, m2, s2):
    # m1, m2 are the means, s1, s2 the variances
    if (np.random.choice([0,1])):
        return np.random.multivariate_normal(m1, [[s1, 0], [0, s1]])
    else:
        return np.random.multivariate_normal(m2, [[s2, 0], [0, s2]])

def getSamples(m1, m2, m3, m4, s, N = 0, M = 0):
    samples = np.zeros((N + M, 2))
    labels = np.zeros(N + M)
    for i in range(N):
        samples[i] = SampleMixtureNormal2D(m1, s, m2, s)
        labels[i] = 1
    for i in range(M):
        samples[i + N] = SampleMixtureNormal2D(m3, s, m4, s)
        labels[i + N] = 0
    return samples, labels

train_input, train_labels = getSamples([0, 1], [1, 0], [0, 0], [1, 1], 0.1, 40, 40)
test_input, test_labels = getSamples([0, 1], [1, 0], [0, 0], [1, 1], 0.1, 40, 40)

# print train_input=

plt.scatter((train_input[train_labels==0])[:, 0], (train_input[train_labels==0])[:, 1],c
plt.scatter((train_input[train_labels==1])[:, 0],(train_input[train_labels==1])[:, 1], c
plt.legend()
plt.title('train set distribution')
plt.show()
```

```
plt.scatter((test_input[test_labels==0])[:, 0], (test_input[test_labels==0])[:, 1],color
plt.scatter((test_input[test_labels==1])[:, 0],(test_input[test_labels==1])[:, 1], color
plt.legend()
plt.title('test set distribution')
plt.show()
```

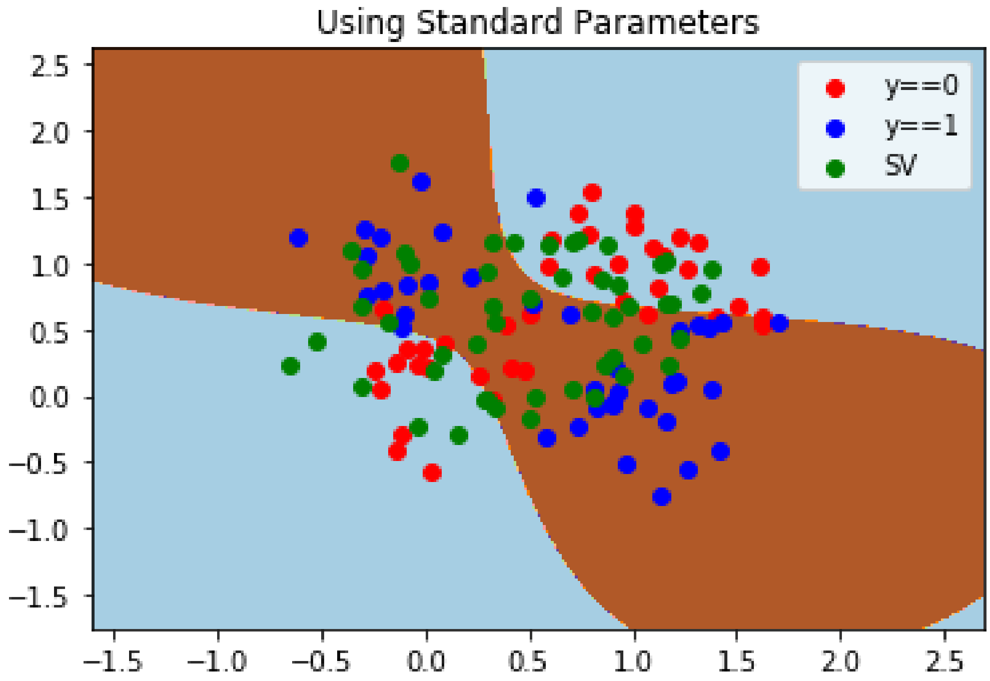




```
In [21]: svc = svm.SVC().fit(train_input, train_labels)
         pred_labels = svc.predict(test_input)
         sv = svc.support_vectors_

         acc = sum(pred_labels == test_labels) * 1.0 / len(test_labels)
         print ("SVM with standard parameters using RBF kernel: acc is %f, num of SVs: %d" % (ac
```

```
SVM with standard parameters using RBF kernel: acc is 0.862500, num of SVs: 51
```

```
In [22]: h = .01  # step size in the mesh
         # create a mesh to plot in
         x_min, x_max = test_input[:, 0].min() - 1, test_input[:, 0].max() + 1
         y_min, y_max = test_input[:, 1].min() - 1, test_input[:, 1].max() + 1

         xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
         Z = svc.predict(np.c_[xx.ravel(), yy.ravel()])

         plt.contourf(xx, yy, Z.reshape(xx.shape), cmap=plt.cm.Paired)
         plt.scatter((test_input[test_labels==0])[:, 0], (test_input[test_labels==0])[:, 1],colo
         plt.scatter((test_input[test_labels==1])[:, 0],(test_input[test_labels==1])[:, 1], colo
         plt.scatter(sv[:,0], sv[:, 1], color='green', label='SV')
         plt.legend()
         plt.title('Using Standard Parameters')
         plt.show()
```

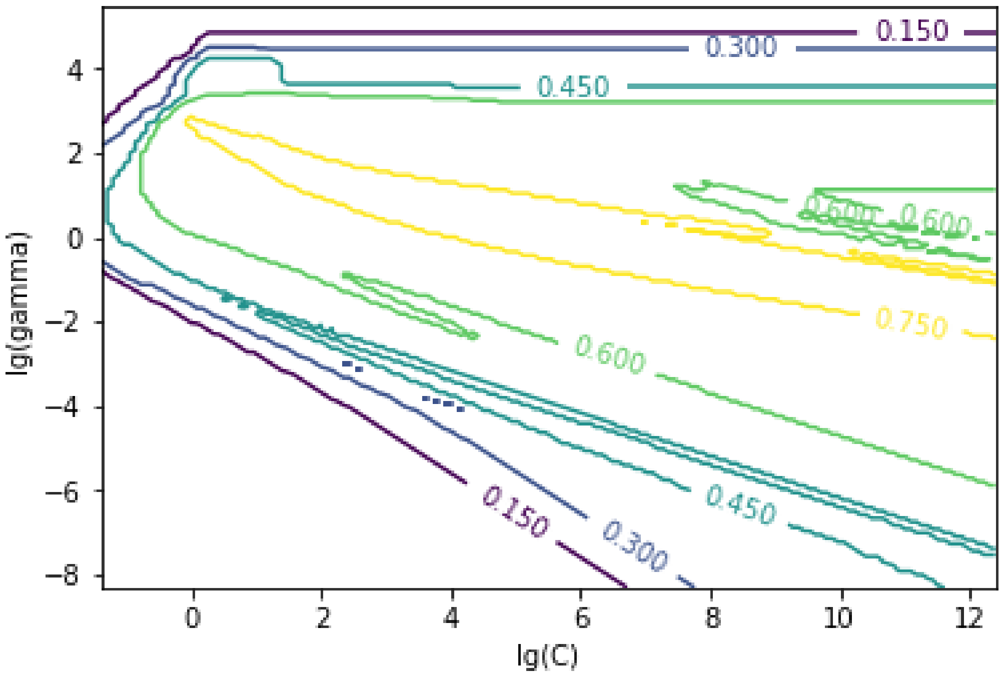


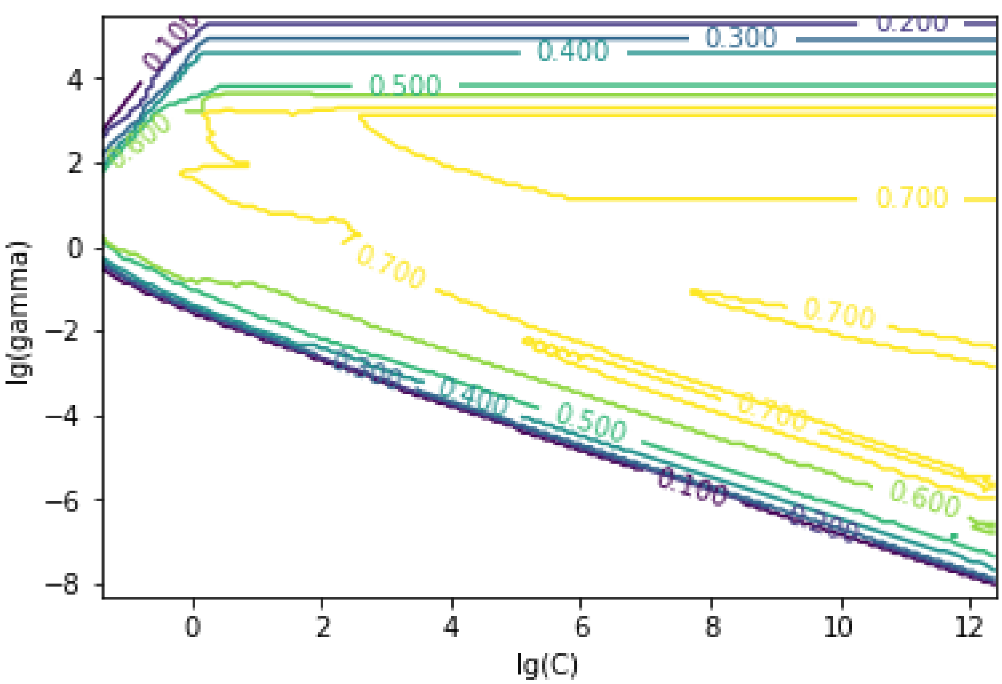
2 H9.3: C-SVM parameter optimization

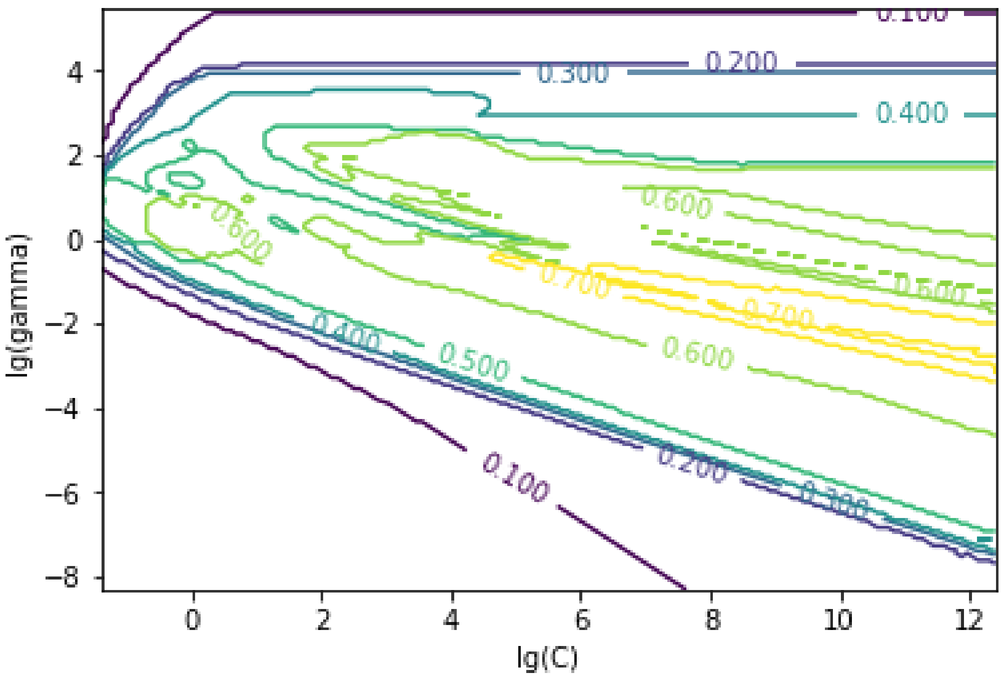
2.1 a

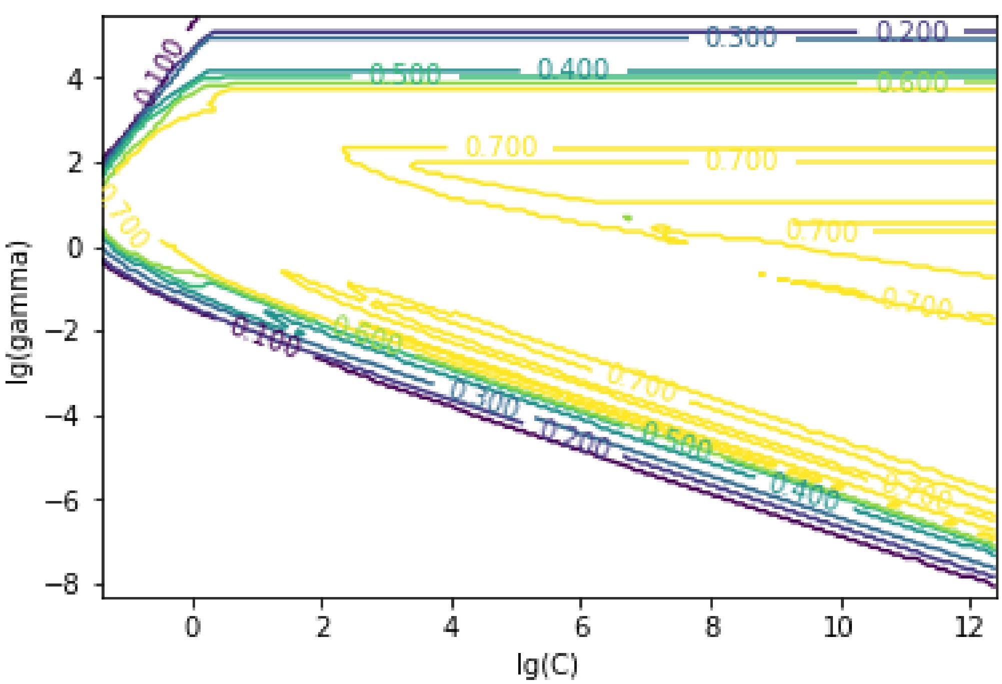
```
In [16]: NC, N_gamma, C0, gamma0, q = 160, 160, 2**-2, 2**-12, 2**0.125
         C_options = np.empty((NC,))
         C_options[0] = C0
         C_options[1:] = q
         C_options = np.cumprod(C_options)
         gamma_options = np.empty((N_gamma,))
         gamma_options[0] = gamma0
         gamma_options[1:] = q
         gamma_options = np.cumprod(gamma_options)
         C, gamma = np.meshgrid(C_options, gamma_options)
         params = np.array(zip(C.flatten(), gamma.flatten()))

         fold = 4
         fold_length = len(train_labels)/fold
         kf = KFold(n_splits=fold)
         kf.get_n_splits(train_input)
         optimal_params = params[0,:]
         best_acc = 0.0

         def calc_acc(test_labels, pred_labels):
             acc = sum(pred_labels == test_labels) * 1.0 / len(test_labels)
             return acc

         for train_index, test_index in kf.split(train_input):
             acc = np.zeros(len(params))
             j = 0
             for param in params:
                 # train
                 svc = svm.SVC(C=param[0], gamma=param[1]).fit(train_input[train_index], train_l
                 pred_labels = svc.predict(train_input[test_index])
                 # predict
                 acc[j] = calc_acc(train_labels[test_index], pred_labels)
                 if(acc[j] == acc.max()):
                     optimal_params = param
                     best_acc = acc[j]
                 j += 1
             acc = acc.reshape(C.shape)
             CS = plt.contour(np.log(C), np.log(gamma),acc)
             plt.clabel(CS, inline=1)
             plt.xlabel('lg(C)')
```

```
    plt.ylabel('lg(gamma)')
    plt.show()
print ("Optimal (C, gamma) is (%f, %f), accuracy is %f" % (optimal_params[0], optimal_p
```






0.100
0.200
0.300
0.400
0.500
0.600
0.700
lg(gamma)
lg(C)


0.100
0.200
0.300
0.400
0.500
0.600
0.700
lg(gamma)
lg(C)

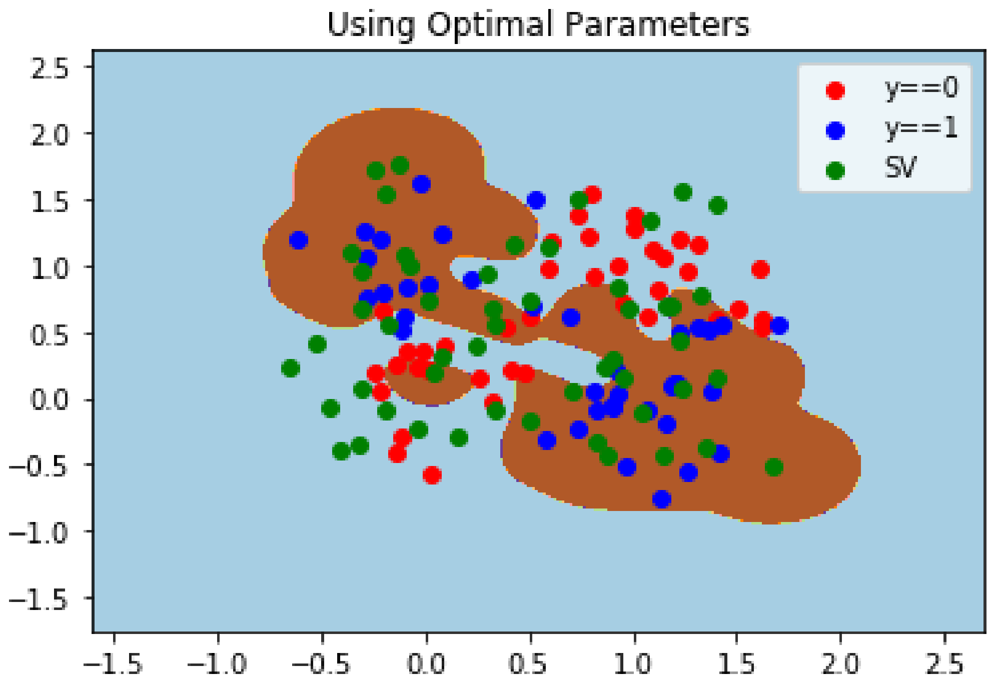
```
Optimal (C, gamma) is (240387.107902, 22.627417), accuracy is 0.800000
```

2.2 b

```
In [30]: # print optimal_params
         svc = svm.SVC(C = optimal_params[0], gamma=optimal_params[1]).fit(train_input, train_la
         pred_labels = svc.predict(test_input)
         sv = svc.support_vectors_
         # print 'num of SVs: %d' % len(sv)
         print ("Accuracy of prediction using optimal parameter: %f, num of SV: %d " % (calc_acc
```

```
Accuracy of prediction using optimal parameter: 0.825000, num of SV: 52
```

```
In [31]: h = .01  # step size in the mesh
         # create a mesh to plot in
         x_min, x_max = test_input[:, 0].min() - 1, test_input[:, 0].max() + 1
         y_min, y_max = test_input[:, 1].min() - 1, test_input[:, 1].max() + 1

         xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
         Z = svc.predict(np.c_[xx.ravel(), yy.ravel()])

         plt.contourf(xx, yy, Z.reshape(xx.shape), cmap=plt.cm.Paired)
         plt.scatter((test_input[test_labels==0])[:, 0], (test_input[test_labels==0])[:, 1],colo
         plt.scatter((test_input[test_labels==1])[:, 0],(test_input[test_labels==1])[:, 1], colo
         plt.scatter(sv[:,0], sv[:, 1], color='green', label='SV')
         plt.title('Using Optimal Parameters')
         plt.legend()
         plt.show()
```



2.3 c

Compared to standard parameters, we got a similar number of support vectors but worse generalization performance. From above graph, we could see obvious overfitting.

If dividing C by 4, we did not see any difference. However, if we diveding gamma by 4, the number of support vectors approximately reduced by half.

```
In [ ]:
```