mi-hw-8-Final

January 5, 2017

1 Support Vector Machines

1.1 Excerscise H8.2 C-SVM with std. parameters

```
In [1]: % matplotlib inline

        import numpy as np
        import scipy as sp
        import math
        import scipy.stats as scp
        import matplotlib as mpl
        from numpy import linalg as la
        from numpy import random as rand
        from matplotlib import pyplot as plt
        from sklearn import svm

In [2]: def create_data(N):
            n = N/2
            n1 = (np.sign(rand.uniform(-1, 1, n))==1).sum()
            n2 = (np.sign(rand.uniform(-1, 1, n))==1).sum()

            X_c1 = np.append(rand.multivariate_normal([0,1], [[0.1, 0], [0, 0.1]],
            X_c2 = np.append(rand.multivariate_normal([0,0], [[0.1, 0], [0, 0.1]],
            # create a data matrix of shape 120x3 where colums 0 and 1 are the dime
            p = np.vstack((X_c1, X_c2))
            #print p.shape
            y = np.vstack((np.zeros((n,1)), np.ones((n,1))))

            return p,y

In [3]: def plot_data(X,y):
            N = len(X[:,0])
            n = N/2
            plt.scatter(X[0:n,0], X[0:n,1], color ='red')
            plt.scatter(X[n+1:N,0], X[n+1:N,1], color='black')

In [35]: def grid_plot_svm (X,y,grid_size,r1,r2,plot_test=False, Xt=0, yt=0):
             # create a grid for the contour plot
```

```
    ran = np.linspace(r1, r2, grid_size)
    GX, GY = np.meshgrid(ran, ran)
    classes = np.zeros((grid_size, grid_size))
    c_svm = svm.SVC()
    c_svm.fit(X,y)

    # go through grid and compute the assigned class
    for gx in range(grid_size):
        for gy in range(grid_size):
            loc = np.vstack((ran[gx],ran[gy])).T
            classes[gx,gy] = c_svm.predict(loc)


    plt.figure()
    plt.contourf(GX, GY, classes[:,:].T, levels=[-1.0,0.,1.0])
    if(plot_test):
        N = len(Xt[:,0])
        n = N/2
        plt.scatter(Xt[0:n,0], Xt[0:n,1], color ='red')
        plt.scatter(Xt[n+1:N,0], Xt[n+1:N,1], color='black')
    else:
        N = len(X[:,0])
        n = N/2
        plt.scatter(X[0:n,0], X[0:n,1], color ='red')
        plt.scatter(X[n+1:N,0], X[n+1:N,1], color='black')

    plt.show()
```

```
In [5]: def loss_error(y,y_pred):
            right = 0
            y_pred.flatten()
            y.flatten()
            for i in range(0,len(y_pred)):
                if (y_pred[i] == y[i]):
                    right = right +1

            return(float(right)/len(y_pred)) * 100
```

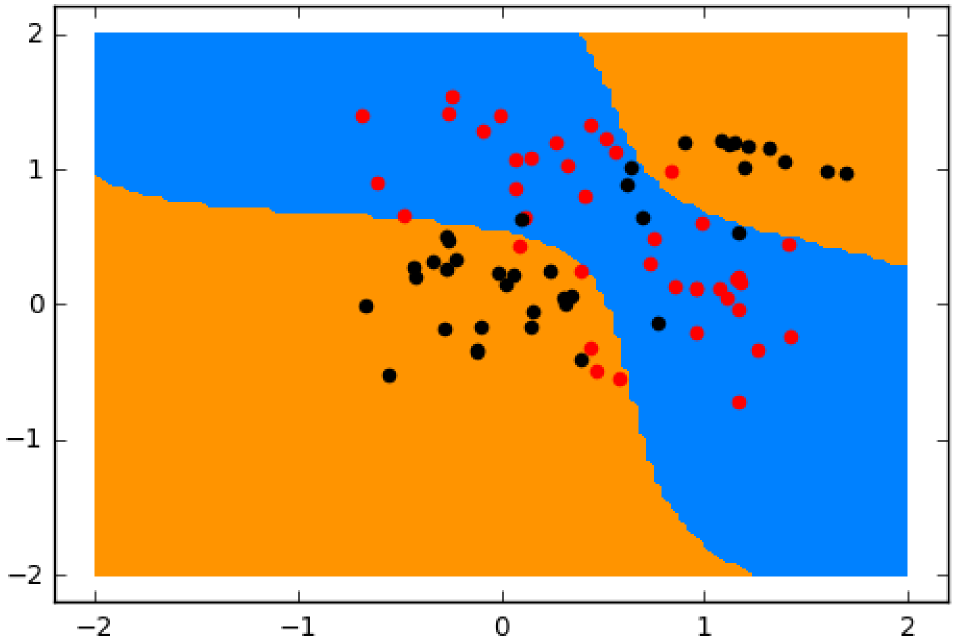
2 Exercise H8.2: C-SVM with standard parameters

In this exercise, we use C-SVMs to solve the “XOR”-classification problem from exercise sheet 6. To this end (1) first create a training set of 80 data as described in exercise H6.1 and (2) create a test set of 80 data from the same distribution.

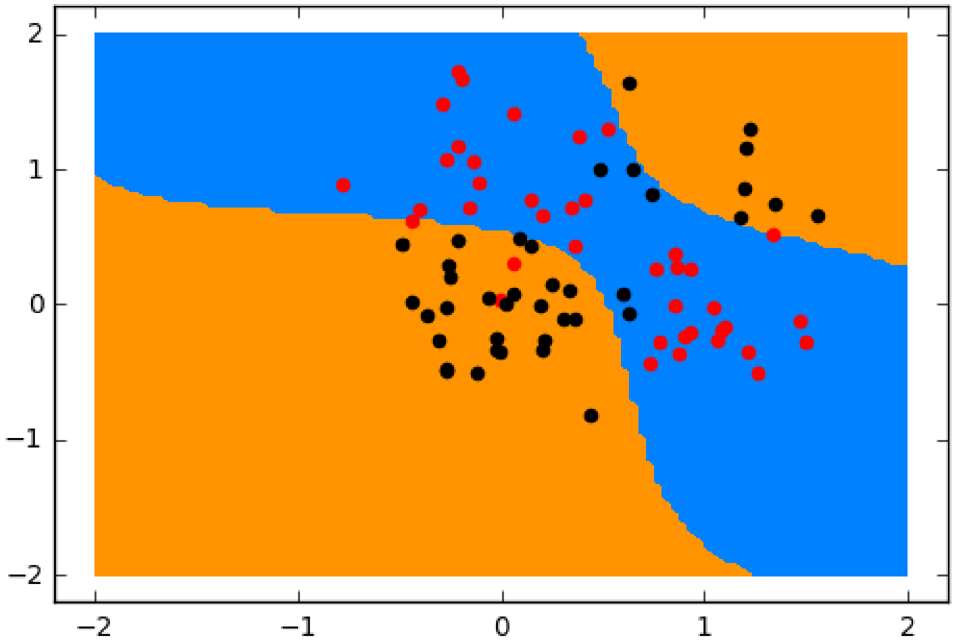
Next, use your chosen SVM implementation to train a C-SVM with RBF kernel and the software's standard parameters. Classify the test data and report the classification error quantified by the 0/1 loss function (percentage of wrong predictions). Visualize the results as in exercise H6.2: plot the training patterns and the decision boundary (e.g. with a contour plot) in input space.

```
In [38]: X_train,y_train = create_data(80)
         X_test,y_test = create_data(80)

         # train svm
         c_svm = svm.SVC()
         c_svm.fit(X_train,y_train)
         print "This model uses ",c_svm.support_vectors_.shape[0], "Support Vectors
         #predict test data
         y_pred = c_svm.predict(X_test)

         # calculate classification error
         error = loss_error(y_test,y_pred)
         print 100-error

         print "\n Plotted with test Data"
         grid_plot_svm(X_train,y_train,100,-2,2,True, X_test,y_test)
         print "\n Plotted with training Data"
         grid_plot_svm(X_train,y_train,100,-2,2)
```

```
This model uses  53 Support Vectors. It missclassification rate is:
13.75

 Plotted with test Data
```



```
Plotted with training Data
```



3 Exercise H8.3: C-SVM parameter optimization

3.1 (a) (2 points) Use cross-validation and grid-search to determine good values for C and the kernel parameter γ.

Follow the procedure described in the guide: Define the grid us- ing exponentially growing sequences of C and γ, e.g. $C \in \{2-6, 2-4, \ldots, 210\}$, $\gamma \in \{2-5, 2-3, \ldots, 29\}$.

Make sure you only use the training data in this step. Plot the mean training-set classification rate and cross-validation performance as a function of C and γ (e.g. using contour plots as in figure 2 of the guide).

```
In [12]: from sklearn.model_selection import cross_val_score
```

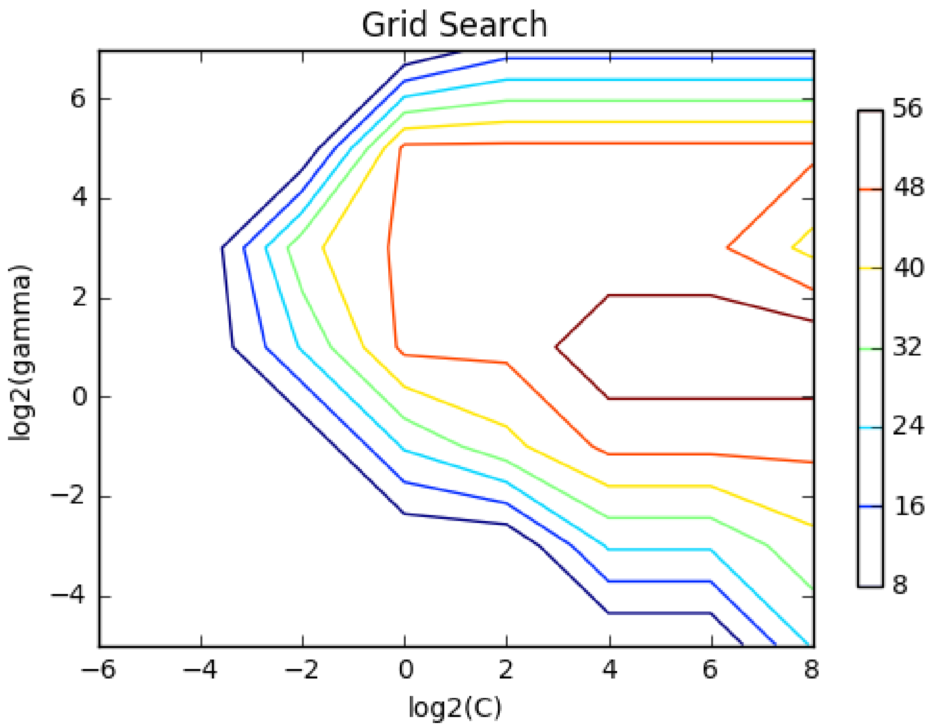
```
In [50]:  def grid_plot_svm_2 (X,y,grid_size,r1,r2,l,c, use_own=False, title=''):
              # create a grid for the contour plot
              ran = np.linspace(r1, r2, grid_size)
              GX, GY = np.meshgrid(ran, ran)
              classes = np.zeros((grid_size, grid_size))
              if(use_own):
                  c_svm = svm.SVC(C=c,gamma=l)
              else:
                  c_svm = svm.SVC()
              c_svm.fit(X,y)
```

```
    # go through grid and compute the assigned class
    for gx in range(grid_size):
        for gy in range(grid_size):
            loc = np.vstack((ran[gx],ran[gy])).T
            classes[gx,gy] = c_svm.predict(loc)

    print "This model uses ",c_svm.support_vectors_.shape[0], "Support Vec

    plt.figure()
    plt.contourf(GX, GY, classes[:,:].T, levels=[-1.0,0.,1.0])
    N = len(X[:,0])
    n = N/2
    plt.scatter(X[0:n,0], X[0:n,1], color ='red')
    plt.scatter(X[n+1:N,0], X[n+1:N,1], color='black')
    plt.title(title)
```

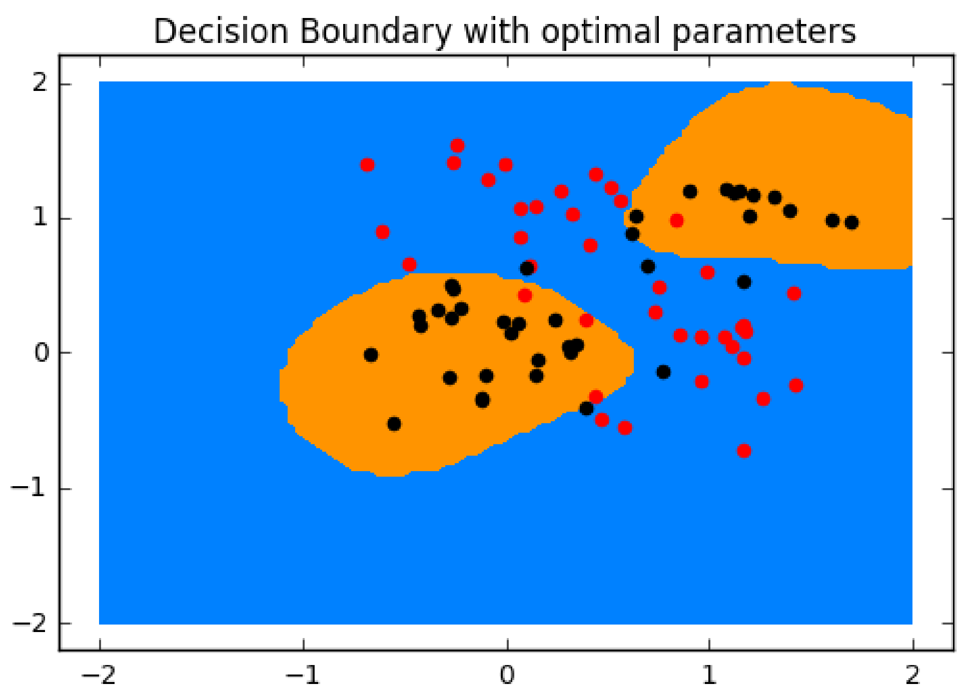
```
In [51]: def cross_valid(X, y, c, g, n_folds=10):
    '''
    Synopsis:
        w_opt, b_opt, lambda_opt = cross_validation(X, Y, L, n_folds=10)
    Arguments:
        X:              2D array of data (features x samples)
        Y:              Vector of true labels (1 x samples)
        L:              List of lambdas to cross validate (1 x #lambdas)
        n_folds:        Number of nested folds
    Output:
        w_opt:          optimal weight vector
        b_opt:          optimal bias
        lambda_opt:     the lambda with the lowest MSE
    '''
    X = X.T
    y = y.T
    d, n = X.shape
    samples_per_fold = int(float(n)/ float(n_folds))

    rates = np.empty(n_folds)
    idx = np.arange(n) # np.random.permutation(n) # np.arange(n)
    for j in range(n_folds):
        # extract one fold for testing
        idx_te = idx[j*samples_per_fold:(j+1)*samples_per_fold]
        # get the train data
        X_tr = np.delete(X, idx_te, axis=1)
        y_tr = np.delete(y, idx_te, axis=1)
        # get the test data
        X_te = X[:,idx_te]
        y_te = y[:,idx_te]
```

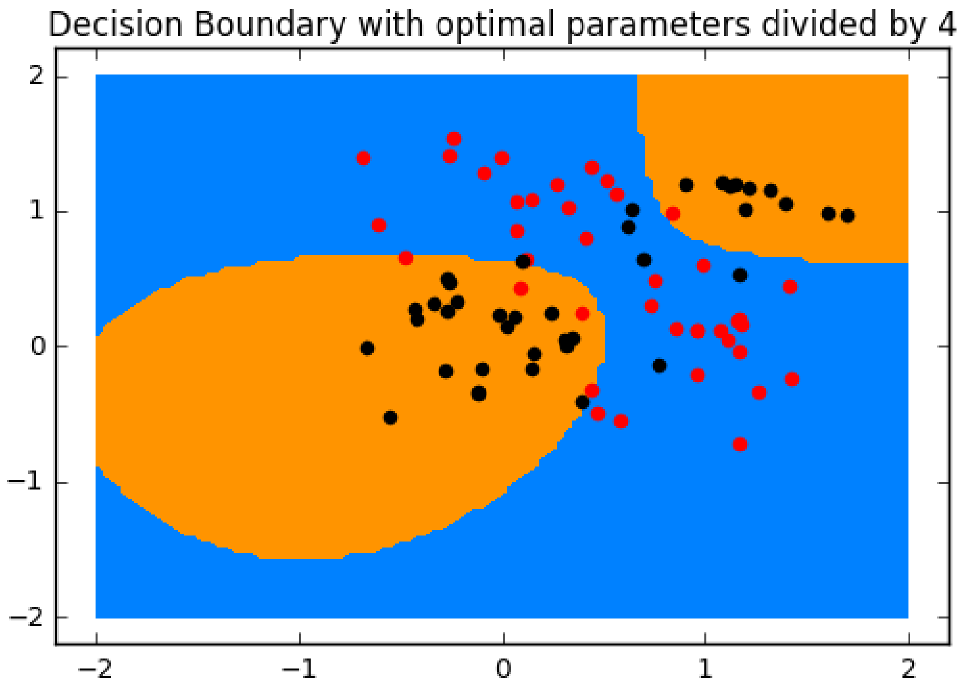
```
            # train the model
            c_svm = svm.SVC(C=c,gamma=g)
            c_svm.fit(X_tr.T,y_tr.T)
            # predict the label
            y_pred = c_svm.predict(X_te.T)

            rates[j] = float(loss_error(y_te.T,y_pred))

        return np.min(rates)
```

In [53]:
```
X_train,y_train = create_data(80)
C = 2.**np.arange(-6,10,2)
G = 2.**np.arange(-5,9,2)

rates = np.zeros((C.shape[0],G.shape[0]))
best_c = 0
best_g = 0
best_rate = 0
for i,c in enumerate(C):
    for j,g in enumerate(G):
        rates[i,j] = cross_valid(X_train,y_train,c,g)
        if (rates[i,j] > best_rate):
            best_rate = rates[i,j];
            best_c = c
            best_g = g


CS = plt.contour(np.log2(C),np.log2(G),rates.T)
CB = plt.colorbar(CS, shrink=0.8, extend='both')
plt.xlabel('log2(C)')
plt.ylabel('log2(gamma)')
plt.title('Grid Search')
plt.show()

grid_plot_svm_2(X_test,y_test,100,-2,2,best_g,best_c,True,"Decision Bounda

grid_plot_svm_2(X_test,y_test,100,-2,2,float(best_g)/float(4),float(best_c
```

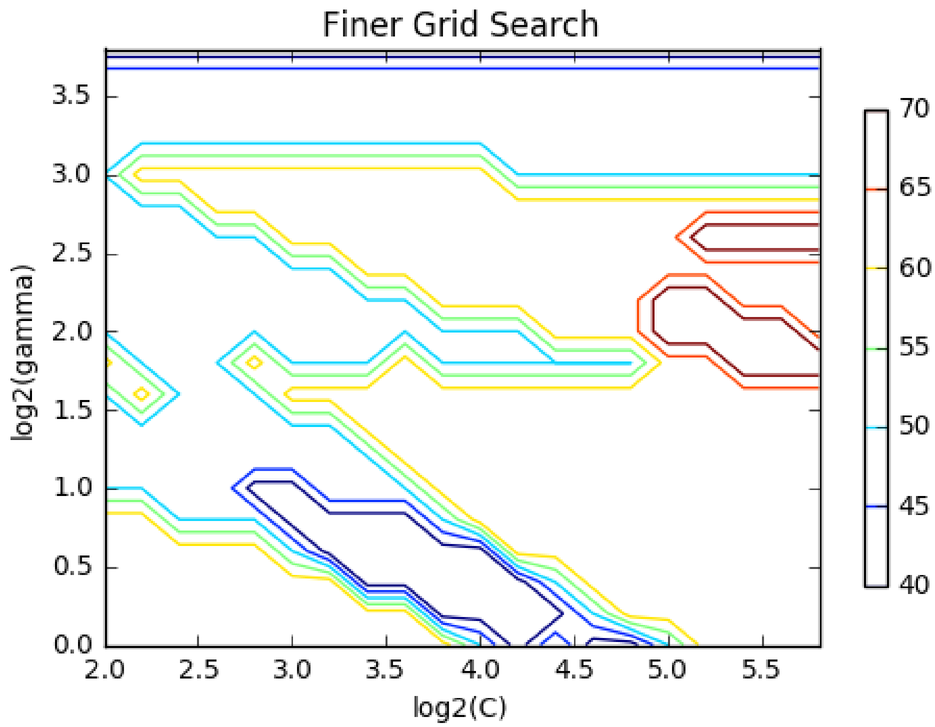



```
This model uses  28 Support Vectors.
This model uses  38 Support Vectors.
```





In [39]:
```
C2 = 2.**np.arange(2,6,0.2)
G2 = 2.**np.arange(0,4,0.2)

rates2 = np.zeros((C2.shape[0],G2.shape[0]))
best_c2 = 0
best_g2 = 0
best_rate2 = 0
for k,c2 in enumerate(C2):
    for l,g2 in enumerate(G2):
        rates2[k,l] = cross_valid(X_train,y_train,c2,g2)
        if (rates2[k,l] > best_rate2):
            best_rate2 = rates2[k,l];
            best_c2 = c2
            best_g2 = g2

CS = plt.contour(np.log2(C2),np.log2(G2),rates2.T)
CB = plt.colorbar(CS, shrink=0.8, extend='both')
plt.xlabel('log2(C)')
plt.ylabel('log2(gamma)')
plt.title('Finer Grid Search')
plt.show()
```


Finer Grid Search
log2(gamma)
log2(C)
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5
70
65
60
55
50
45
40