SVM神经网络中的参数优化---如何更好的提升分类器的性能

该案例作者申明：

1：本人长期驻扎在此板块里，对该案例提问，做到有问必答。本套书籍官方网站为：video.ourmatlab.com

2：点此从当当预定本书：《Matlab神经网络30个案例分析》。

3：此案例有配套的教学视频，视频下载方式video.ourmatlab.com/vbuy.html。

4：此案例为原创案例，转载请注明出处（《Matlab神经网络30个案例分析》）。

5：若此案例碰巧与您的研究有关联，我们欢迎您提意见，要求等，我们考虑后可以加在案例里。

by liyang[faruto] @ faruto's Studio~ Email:faruto@163.com QQ:516667408
http://blog.sina.com.cn/faruto http://www.matlabsky.com http://www.mfun.la
http://video.ourmatlab.com

Contents

清空环境变量

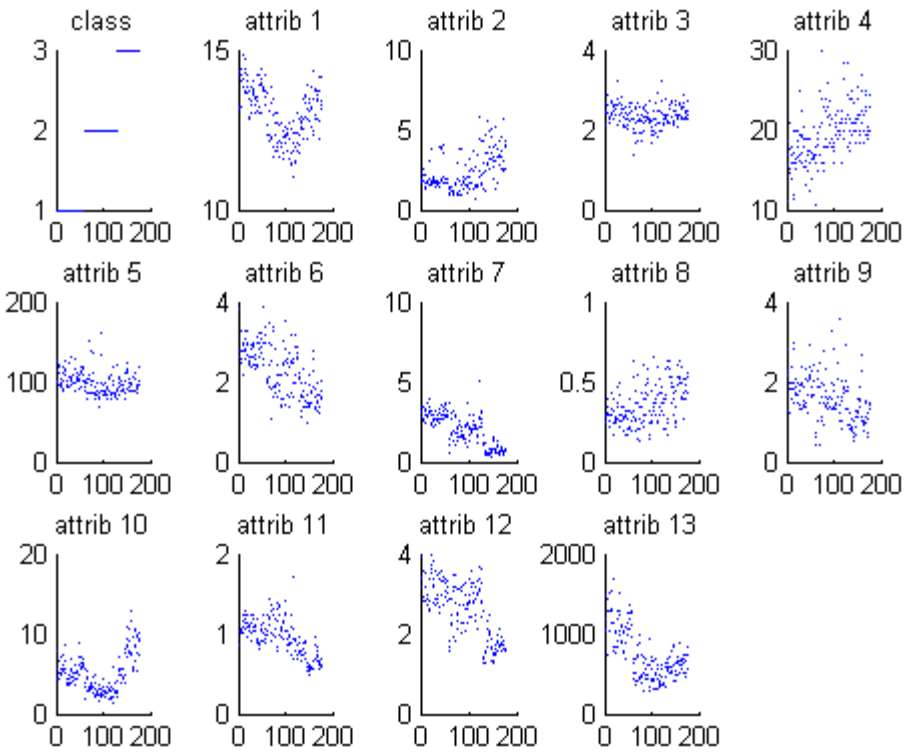
```
function chapter13
```

```
close all;
clear;
clc;
format compact;
```

数据的提取和预处理

```
% 载入测试数据wine,其中包含的数据为classnumber = 3,wine:178*13的矩阵,wine_labes:178*1的列向量
load chapter13_wine.mat;

% 画出测试数据的可视化图
figure
subplot(3,5,1);
hold on
for run = 1:178
    plot(run,wine_labels(run));
end
title('class','FontSize',10);

for run = 2:14
    subplot(3,5,run);
    hold on;
    str = ['attrib ',num2str(run-1)];
    for i = 1:178
        plot(i,wine(i,run-1));
    end
    title(str,'FontSize',10);
end

% 选定训练集和测试集
```

```
% 将第一类的1-30,第二类的60-95,第三类的131-153做为训练集
train_wine = [wine(1:30,:);wine(60:95,:);wine(131:153,:)];
% 相应的训练集的标签也要分离出来
train_wine_labels = [wine_labels(1:30);wine_labels(60:95);wine_labels(131:153)];
% 将第一类的31-59,第二类的96-130,第三类的154-178做为测试集
test_wine = [wine(31:59,:);wine(96:130,:);wine(154:178,:)];
% 相应的测试集的标签也要分离出来
test_wine_labels = [wine_labels(31:59);wine_labels(96:130);wine_labels(154:178)];

% 数据预处理,将训练集和测试集归一化到[0,1]区间

% mapminmax为matlab自带的映射函数
[train_wine,pstrain] = mapminmax(train_wine');
% 将映射函数的范围参数分别置为0和1
pstrain.ymin = 0;
pstrain.ymax = 1;
% 对训练集进行[0,1]归一化
[train_wine,pstrain] = mapminmax(train_wine,pstrain);

% mapminmax为matlab自带的映射函数
[test_wine,pstest] = mapminmax(test_wine');
% 将映射函数的范围参数分别置为0和1
pstest.ymin = 0;
pstest.ymax = 1;
% 对测试集进行[0,1]归一化
[test_wine,pstest] = mapminmax(test_wine,pstest);

% 对训练集和测试集进行转置,以符合libsvm工具箱的数据格式要求
train_wine = train_wine';
test_wine = test_wine';
```

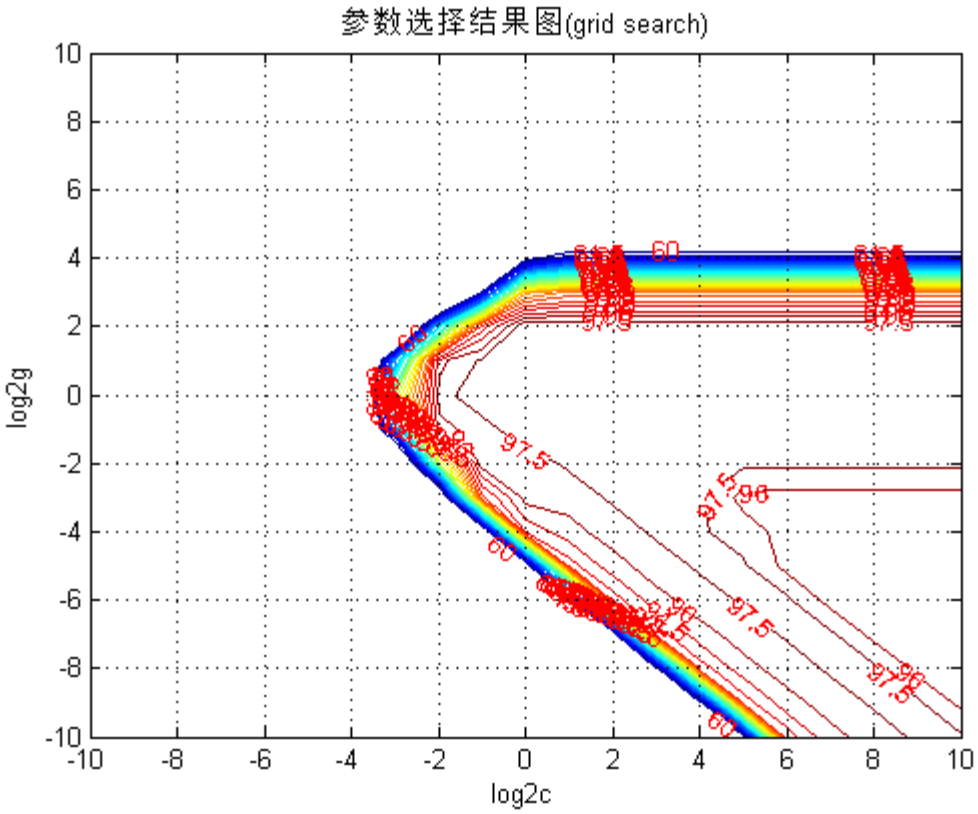


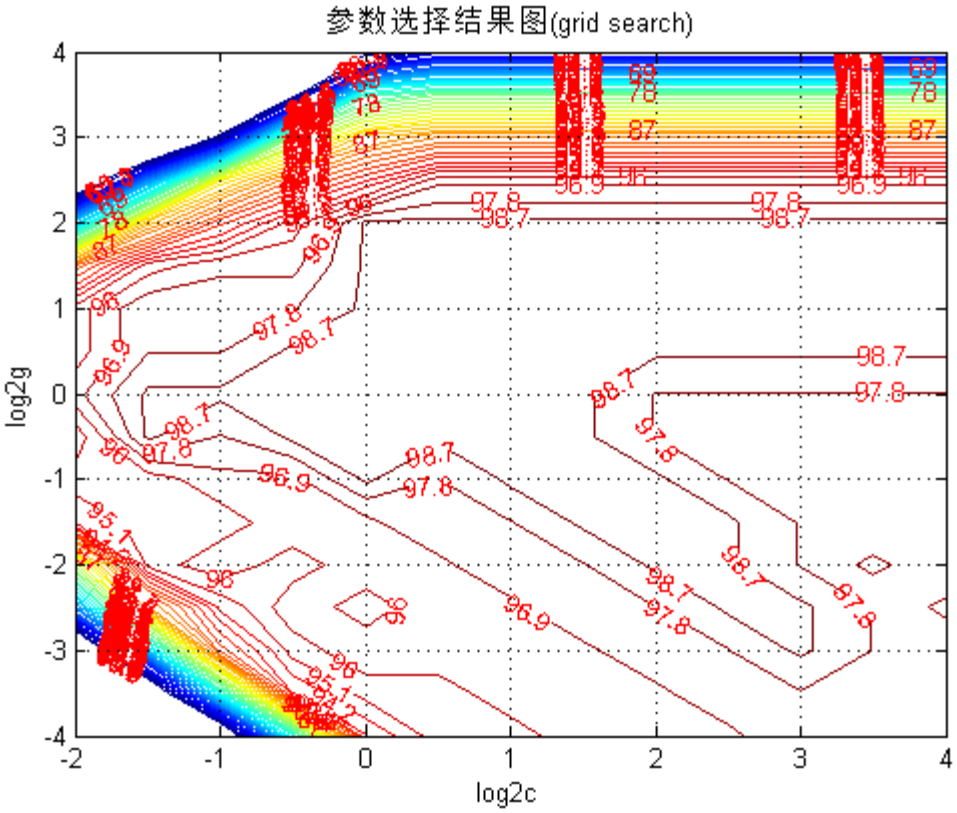
选择最佳的SVM参数c&g

```
% 首先进行粗略选择: c&g 的变化范围是 2^(-10),2^(-9),...,2^(10)
[bestacc,bestc,bestg] = SVMcgForClass(train_wine_labels,train_wine,-10,10,-10,10);

% 打印粗略选择结果
disp('打印粗略选择结果');
str = sprintf( 'Best Cross Validation Accuracy = %g%% Best c = %g Best g =
%g',bestacc,bestc,bestg);
disp(str);
```

```
% 根据粗略选择的结果图再进行精细选择: c 的变化范围是 2^(-2),2^(-1.5),...,2^(4), g 的变化范围是 2^(-4),2^(-3.5),...,2^(4),
[bestacc,bestc,bestg] = SVMcgForClass(train_wine_labels,train_wine,-2,4,-4,4,3,0.5,0.5,0.9);
% 打印精细选择结果
disp('打印精细选择结果');
str = sprintf( 'Best Cross Validation Accuracy = %g%% Best c = %g Best g = %g',bestacc,bestc,bestg);
disp(str);
```

```
打印粗略选择结果
Best Cross Validation Accuracy = 98.8764% Best c = 0.5 Best g = 1
打印精细选择结果
Best Cross Validation Accuracy = 98.8764% Best c = 0.353553 Best g = 0.707107
```





利用最佳的参数进行SVM网络训练

```
cmd = ['-c ',num2str(bestc),' -g ',num2str(bestg)];
model = svmtrain(train_wine_labels,train_wine,cmd);
```

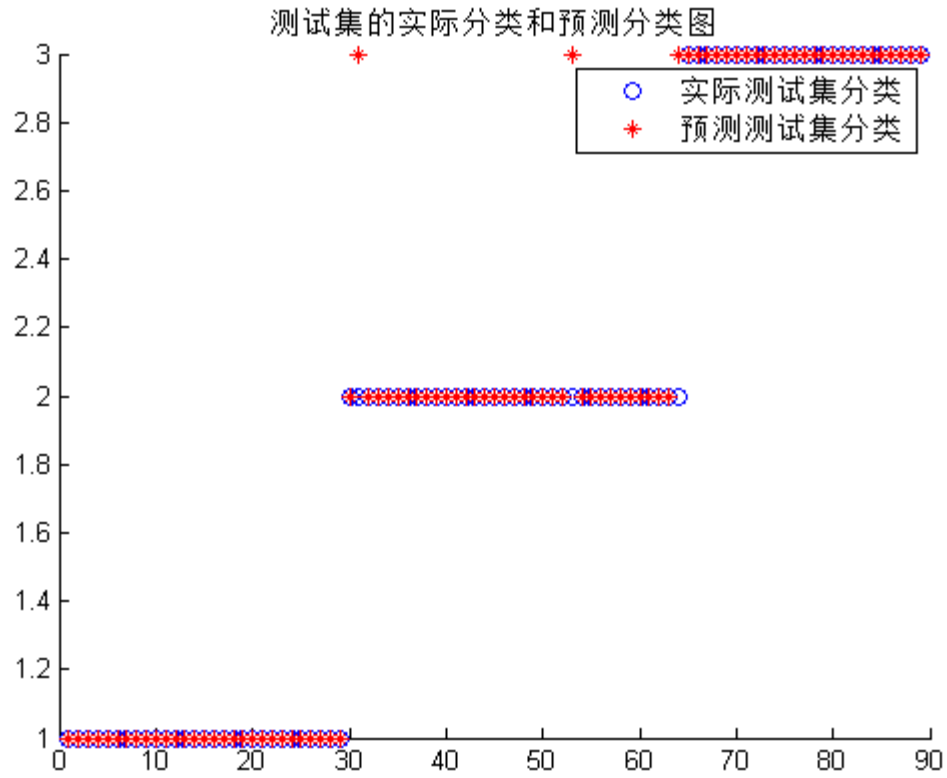
SVM网络预测

```
[predict_label,accuracy] = svmpredict(test_wine_labels,test_wine,model);

% 打印测试集分类准确率
total = length(test_wine_labels);
right = sum(predict_label == test_wine_labels);
disp('打印测试集分类准确率');
str = sprintf( 'Accuracy = %g%% (%d/%d)',accuracy(1),right,total);
disp(str);
```

```
Accuracy = 96.6292% (86/89) (classification)
打印测试集分类准确率
Accuracy = 96.6292% (86/89)
```

结果分析

```
% 测试集的实际分类和预测分类图
% 通过图可以看出只有三个测试样本是被错分的
figure;
hold on;
plot(test_wine_labels,'o');
plot(predict_label,'r*');
legend('实际测试集分类','预测测试集分类');
title('测试集的实际分类和预测分类图','FontSize',10);
snapnow;

% web http://www.matlabsky.com/forum-31-1.html
web http://www.matlabsky.com/forum-31-1.html -new;
```



子函数 **SVMcgForClass.m**

```
function [bestacc,bestc,bestg] =
SVMcgForClass(train_label,train,cmin,cmax,gmin,gmax,v,cstep,gstep,accstep)
% SVMcgForClass
% 输入:
% train_label:训练集标签.要求与libsvm工具箱中要求一致.
% train:训练集.要求与libsvm工具箱中要求一致.
% cmin:惩罚参数c的变化范围的最小值(取以2为底的对数后),即 c_min = 2^(cmin).默认为 -5
% cmax:惩罚参数c的变化范围的最大值(取以2为底的对数后),即 c_max = 2^(cmax).默认为 5
% gmin:参数g的变化范围的最小值(取以2为底的对数后),即 g_min = 2^(gmin).默认为 -5
% gmax:参数g的变化范围的最小值(取以2为底的对数后),即 g_min = 2^(gmax).默认为 5
% v:cross validation的参数,即给测试集分为几部分进行cross validation.默认为 3
% cstep:参数c步进的大小.默认为 1
% gstep:参数g步进的大小.默认为 1
% accstep:最后显示准确率图时的步进大小.默认为 1.5
% 输出:
% bestacc:Cross Validation 过程中的最高分类准确率
% bestc:最佳的参数c
% bestg:最佳的参数g

% about the parameters of SVMcgForClass
if nargin < 10
    accstep = 1.5;
end
if nargin < 8
    accstep = 1.5;
    cstep = 1;
    gstep = 1;
end
if nargin < 7
    accstep = 1.5;
    v = 3;
    cstep = 1;
    gstep = 1;
end
if nargin < 6
    accstep = 1.5;
    v = 3;
    cstep = 1;
    gstep = 1;
    gmax = 5;
end
```

```
if nargin < 5
    accstep = 1.5;
    v = 3;
    cstep = 1;
    gstep = 1;
    gmax = 5;
    gmin = -5;
end
if nargin < 4
    accstep = 1.5;
    v = 3;
    cstep = 1;
    gstep = 1;
    gmax = 5;
    gmin = -5;
    cmax = 5;
end
if nargin < 3
    accstep = 1.5;
    v = 3;
    cstep = 1;
    gstep = 1;
    gmax = 5;
    gmin = -5;
    cmax = 5;
    cmin = -5;
end
% X:c Y:g cg:accuracy
[X,Y] = meshgrid(cmin:cstep:cmax,gmin:gstep:gmax);
[m,n] = size(X);
cg = zeros(m,n);
% record accuracy with different c & g,and find the best accuracy with the smallest c
bestc = 0;
bestg = 0;
bestacc = 0;
basenum = 2;
for i = 1:m
    for j = 1:n
        cmd = ['-v ',num2str(v),' -c ',num2str( basenum^X(i,j) ),' -g ',num2str(
basenum^Y(i,j) )];
        cg(i,j) = svmtrain(train_label, train, cmd);

        if cg(i,j) > bestacc
            bestacc = cg(i,j);
            bestc = basenum^X(i,j);
            bestg = basenum^Y(i,j);
        end
        if ( cg(i,j) == bestacc && bestc > basenum^X(i,j) )
            bestacc = cg(i,j);
            bestc = basenum^X(i,j);
            bestg = basenum^Y(i,j);
        end

    end
end
% draw the accuracy with different c & g
figure;
[C,h] = contour(X,Y,cg,60:accstep:100);
clabel(C,h,'FontSize',10,'Color','r');
xlabel('log2c','FontSize',10);
ylabel('log2g','FontSize',10);
title('参数选择结果图(grid search)','FontSize',10);
grid on;
```

SVM神经网络中的参数优化---如何更好的提升分类器的性能

Published with MATLAB® 7.11