Tai Duc Nguyen - ECEC 487 - 10/26/2019

- Homework Part 0
 - a. What accuracy do you obtain?
 - Compare the accuracy of your solution with the example solution. If they differ, explain why. If they are the same, explain why
 - Show the digits at the beginning of the demo is an excellent visualization to confirm the inputs are correct. What would be a good visualization to validate the classification results?
 - Extra credit: implement your visualization suggestion
- Homework Part 1 (Next Page)

Homework Part 0

a. What accuracy do you obtain?

Attempt 1: 98.80%

Attempt 2: 98.96%

Attempt 3: 99.00%

Attempt 4: 98.72%

Attempt 5: 98.92%

Compare the accuracy of your solution with the example solution. If they differ, explain why. If they are the same, explain why

The accuracies obtained from my solution is different from that of the example solution (98.72%). These small differences are due to the randomized initial weights and biases at each neuron. Although the sensitivity of the network can tolerate different initializations through the **Batch Normalization Layer**, the network's outputs are still subjected to its initial conditions.

Show the digits at the beginning of the demo is an excellent visualization to confirm the inputs are correct. What would be a good visualization to validate the classification results?

A good visualization to validate the classification results can be made from a collage of:

- For each digits (0...10)
 - Wrong classifications and their original images
 - One correct classification and its original image

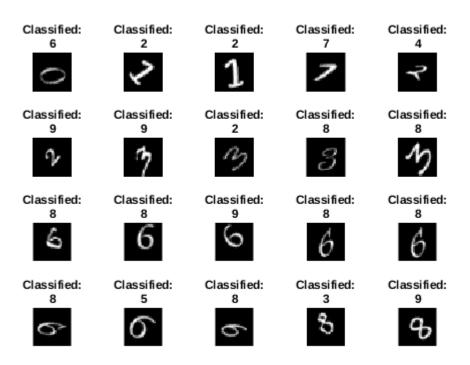
Extra credit: implement your visualization suggestion

```
WrongPred = YPred ~= YValidation;
WrongPredCatg = YPred(WrongPred);

WrongImg = find(WrongPred == 1);

figure;
sgtitle('20 Incorrect Classifications')
for i = 1:20
    subplot(4,5,i);
    imshow(imdsValidation.Files{WrongImg(i)});
    title(['Classified: ', WrongPredCatg(i)])
end
```

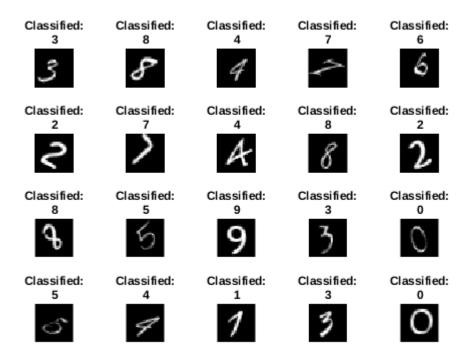
20 Incorrect Classifications



```
CorrectPred = YPred == YValidation;
CorrectPredCatg = YPred(CorrectPred);
idx=randperm(length(CorrectPredCatg));
CorrectImg = find(CorrectPred == 1);
```

```
figure;
sgtitle('20 Correct Classifications')
for i = 1:20
    subplot(4,5,i);
    imshow(imdsValidation.Files{CorrectImg(idx(i))});
    title(['Classified: ', CorrectPredCatg(idx(i))])
end
```

20 Correct Classifications



Homework Part 1 (Next Page)

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```
close all; clear all;
```

Problem 4.6 Page 248

```
m = [-5 5 5 -5; 5 -5 5 -5];
s = 2;
N = 100;

randn('seed',0);
[x1, y1] = data_generator(m,s,N);

randn('seed',10);
[x2, y2] = data_generator(m,s,N);

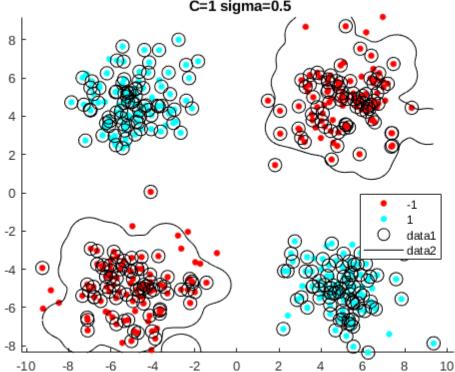
tol = 0.001;

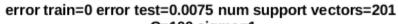
C = [1 100 1000 1000];
sigma = [0.5 1 2 4];
```

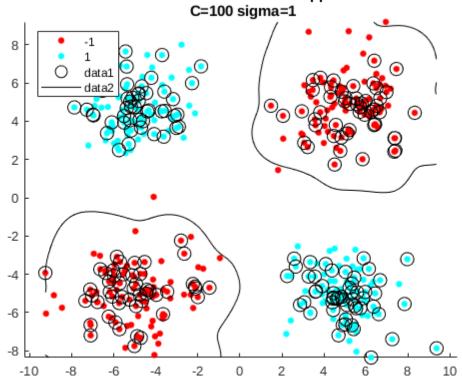
Use example code for plotting the support vectors from

https://www.mathworks.com/help/stats/fitcsvm.html#bvdn8ei-1

```
d = 0.02;
[x1Grid, x2Grid] = meshgrid(min(x2(1,:)):d:max(x2(1,:)),...
    min(x2(2,:)):d:max(x2(2,:)));
xGrid = [x1Grid(:), x2Grid(:)];
for i=1:length(C)
    [svm,pe\_tr,pe\_te] = SVM\_class(x1,y1,x2,y2,tol,C(i),sigma(i));
    [~,scores1] = predict(svm,xGrid);
    figure
    hold on
    h(1:2) = gscatter(x2(1,:),x2(2,:),y2);
    h(3) = plot(x2(1,svm.IsSupportVector),x2(2,svm.IsSupportVector),'ko','MarkerSize',10);
    % Support vectors
    contour(x1Grid,x2Grid,reshape(scores1(:,2),size(x1Grid)),[0 0],'k');
    title({['error train=',num2str(pe_tr),' error test=',num2str(pe_te),...
        ' num support vectors=',num2str(length(svm.SupportVectors))],...
        [' C=',num2str(C(i)),' sigma=',num2str(sigma(i))]});
```







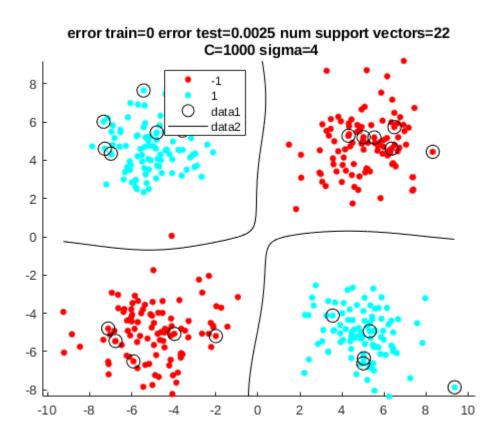
error train=0 error test=0.0025 num support vectors=68 C=1000 sigma=2

-2

0

2

10



Decision Tree Exercise

-8 <u>L</u> -10

-8

[%] This excercise will be completed with a larger dataset because the % prunning effect is not easy to be seen when the dataset is small.

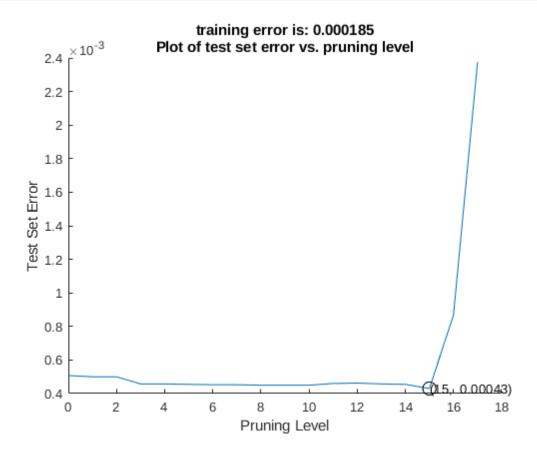
```
randn('seed',0);
[x1, y1] = data generator(m, s, N*1000);
randn('seed',10);
[x2, y2] = data_generator(m,s,N*1000);
maxSplit = 100;
dectree = fitctree(x1',y1','MaxNumSplits',maxSplit);
train_res = predict(dectree,x1');
pe_tr = sum(y1'~=train_res)/length(y1);
L = max(dectree.PruneList);
er = zeros(max(dectree.PruneList),1);
test res = predict(dectree, x2');
pe te = sum(y2'\sim=test res)/length(y2);
er(1) = pe_te;
for j=2:max(dectree.PruneList)
    dectree = prune(dectree, 'level',1);
    test res = predict(dectree,x2');
    pe_te = sum(y2'~=test_res)/length(y2);
    er(j) = pe te;
end
figure
hold on
er t = 0:1:L-1;
plot(er t,er)
title({['training error is: ', num2str(pe_tr)],...
    ['Plot of test set error vs. pruning level']})
xlabel('Pruning Level');
ylabel('Test Set Error')
[v,i] = min(er);
plot(er_t(i),er(i),'ko','MarkerSize',10);
text(er_t(i),er(i),['(' num2str(er_t(i)) ', ' num2str(er(i)) ')'])
```

Conclusions from previous Exercises

The Support Vector Machine algorithm is evaluated with different number of C (box constraint) and sigma (kernel scale). It is apparent that increasing C will result in a lesser number of support vectors. The same relationship also applies for sigma.

```
% From the experiment above, the lowest error test of the SVM is 0.0025 % with a dataset of 400 points.
% However, the Decision Tree algorithm results in a much lower error rate % 0.00043 for a larger dataset of 400*1000=400,000 points.
% With regards to the Decision Tree algorithm, the pruning level does have % an impact to the accuracy, however, dependent on the split-level and the % minimum leaf size after training because if the depth of the tree is % shallow, then removing leaves will remove necessary decisions. Hence, the % code above chose a large dataset and the maximum number of split is high % (100).
```

```
function [x,y] = data_generator(m,s,N)
    S = s*eye(2);
    [l,c] = size(m);
    x = []; % Creating the training set
    for i = 1:c
        x = [x mvnrnd(m(:,i)',S,N)'];
    end
    y=[ones(1,N) ones(1,N) -ones(1,N)];
end
```



[Function] Using the SVM Classifier from textbook CX 4.5 Page 247 with modifications

```
function [svm,pe_tr,pe_te] = SVM_class(X1,y1,X2,y2,tol,C,sigma)
    svm = fitcsvm(X1', y1','KernelFunction','rbf',...
    'KernelScale',sigma,'BoxConstraint',C,...
    'Solver','SMO','KKTTolerance',tol,...
    'IterationLimit',20000,'CacheSize',10000);

%Computation of the error probability
    train_res = predict(svm,X1');
    pe_tr = sum(y1'~=train_res)/length(y1);
    test_res = predict(svm,X2');
    pe_te = sum(y2'~=test_res)/length(y2);
end
```