CSE 5523 HW 3

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1. Problem 1

I use a HoldOut method for cross validation. 90% of training dataset is for training, 10% of training dataset is to calculate training error.

Bagged_10 means there are 10 number of trees.

Boosted_100 means 100 ensemble learning cycles.

	Decision	Bagged_10	Bagged_15	Bagged_20	Boosted_50	Boosted_100	Boosted_150	Boosted_200
Training Error	0.0550	0.0600	0.0300	0.0200	0.0600	0.0350	0.0300	0.0350
Testing Error	0.0475	0.0350	0.0210	0.0245	0.0615	0.0505	0.0495	0.0435

Usually, as the increase of number of tree increases or number of learning cycles, both training error and testing error will decrease and better than decision tree.

Decision Tree Code:

```
Y = [ones(1000, 1); -ones(1000, 1)];
load('train79.mat');
trainData = d79;
load('test79.mat');
testData = d79;

N = size(trainData, 1);
M = size(trainData, 2);
percent = 0.1;
[TrainInd, TestInd] = crossvalind(N, percent);
trainTrainN = size(TrainInd, 1);
trainTestN = size(TestInd, 1);
trainTrainData = zeros(trainTrainN, M);
trainTrainYs = zeros(trainTrainN, 1);
trainTestData = zeros(trainTestN, M);

for i = 1: trainTrainN
    trainTrainData(i, :) = trainData(TrainInd(i), :);
    if TrainInd(i) <= 1000
        trainTrainYs(i) = 1;
    else
        trainTrainYs(i) = -1;
    end
end
for i = 1: trainTestN
    trainTestData(i, :) = trainData(TestInd(i), :);
end

tree = fitctree(trainTrainData, trainTrainYs);
predTrainLabels = predict(tree, trainTestData);
trainError = 0;
for i = 1 : trainTestN
    if TestInd(i) <= 1000
        trueLabel = 1;
    else
        trueLabel = -1;
    end
    if predTrainLabels(i) ~= trueLabel
        trainError = trainError + 1;
    end
end
trainError = trainError / trainTestN

testN = size(testData, 1);
predTestLabels = predict(tree, testData);
```

```
testError = 0;
for i = 1: testN
    if i <= 1000
        trueLabel = 1;
    else
        trueLabel = -1;
    end
    if predTestLabels(i) ~= trueLabel
        testError = testError + 1;
    end
end
testError = testError / testN
```

Bagged Tree Code:

```
treeNum = 20;
B = TreeBagger(treeNum, trainTrainData, trainTrainYs);
predTrainLabels = predict(B, trainTestData);
trainError = 0;

for i = 1 : trainTestN
    if TestInd(i) <= 1000
        trueLabel = 1;
    else
        trueLabel = -1;
    end
    if str2double(predTrainLabels{i}) ~= trueLabel
        trainError = trainError + 1;
    end
end
trainError = trainError * 1.0 / trainTestN

testN = size(testData, 1);
predTestLabels = predict(B, testData);
testError = 0;
for i = 1: testN
    if i <= 1000
        trueLabel = 1;
    else
        trueLabel = -1;
    end
    if str2double(predTestLabels{i}) ~= trueLabel
        testError = testError + 1;
    end
end
testError = testError * 1.0 / testN
```

Boosted Tree Code:

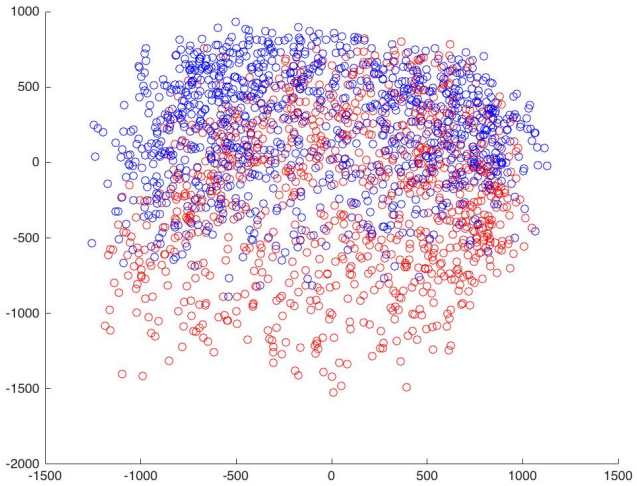
```
ens = fitensemble(trainTrainData, trainTrainYs, 'AdaBoostM1', 200, 'Tree');
predTrainLabels = predict(ens, trainTestData);
trainError = 0;
for i = 1 : trainTestN
    if TestInd(i) <= 1000
        trueLabel = 1;
    else
        trueLabel = -1;
    end
    if predTrainLabels(i) ~= trueLabel
        trainError = trainError + 1;
    end
end
trainError = trainError * 1.0 / trainTestN

testN = size(testData, 1);
predTestLabels = predict(ens, testData);
```

```
testError = 0;
for i = 1: testN
    if i <= 1000
        trueLabel = 1;
    else
        trueLabel = -1;
    end
    if predTestLabels(i) ~= trueLabel
        testError = testError + 1;
    end
end
testError = testError * 1.0 / testN
```

2. Problem 2

(1) The visualization figure is shown below. This is performed on the training data.



Code is shown below:

```
load('train79.mat');
trainData = d79;

trainData = bsxfun(@minus, trainData, mean(trainData, 1));
C = cov(trainData);

[V D] = eig(C);
[D order] = sort(diag(D), 'descend');
V = V(:, order);

trainData = trainData * V(:, 1: 2);
cdata = [ones(1000, 1) * [1 0 0]; ones(1000, 1) * [0 0 1]];
size(trainData)
scatter(trainData(:, 1), trainData(:, 2), 'o', 'cdata', cdata)
```

(2) Figure of Class 7 is shown below. It seems that it captures two type of 7s in each figure.

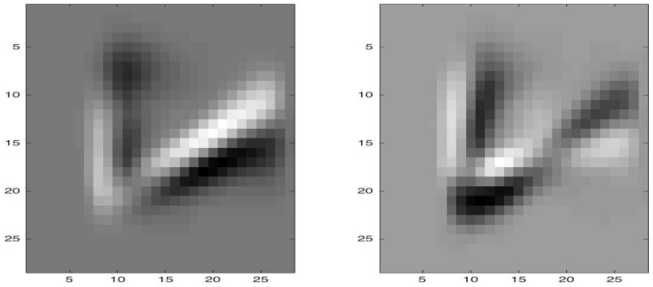


Figure of Class 9 is shown below. It seems that it captures two type of 9s in each figure.

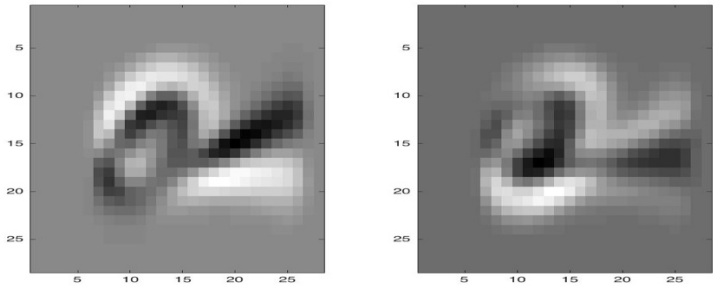
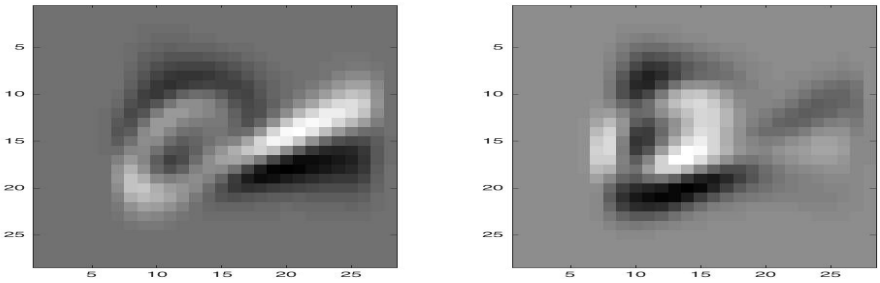


Figure of both classes are shown below. It seems the left figure captures 9 and another figure captures 7.



Code is shown below:

```
load('train79.mat');
trainData = d79;
load('test79.mat');
testData = d79;
X1 = [trainData(1: 1000, :); testData(1: 1000, :)];
X2 = [trainData(1001: 2000, :); testData(1001: 2000, :)];
X3 = [X1; X2];
X = X3;

X = X';
X = bsxfun(@minus, X, mean(X, 2));
s = cov(X');
[V, D] = eig(s);
[D order] = sort(diag(D), 'descend');
V = V(:, order);

figure,subplot(1, 2, 1)
colormap gray
for i = 1:2
    subplot(1, 2, i)
```

```
        imagesc(reshape(V(:, i), 28, 28))
    end
```

3. Problem 3

I run clustering algorithms on test dataset.

The error rate is calculated in the following way, for the first 1000 images, I will pick up the largest cluster, all points out of the largest cluster is classified as error. The same for the later 1000 pages. The error rate is shown below. It shows that single-linkage is much better than k-means, possible reason is that cluster function constructs a maximum of n clusters using the 'distance' criterion and don't guarantee that the number of clusters generated is same as setting. Both method's error rate is increasing with cluster num, which is a characteristic of our metric.

Number of clusters	2	5	10	50
k-means	0.3965	0.7400	0.7700	0.9325
Single-linkage	5.0000e-04	0.0020	0.0050	0.0260

Code for K-means:

```
load('test79.mat');
testData = d79;

ks = [2, 5, 10, 50];
for kIdx = 1: size(ks, 2)
    error = 0;
    k = ks(kIdx);
    clusterLabels = kmeans(testData, k);
    clusterNums = zeros(k, 1);
    for i = 1: 1000
        label = clusterLabels(i);
        clusterNums(label) = clusterNums(label) + 1;
    end
    [maxVal, maxIdx] = max(clusterNums);
    error = 1000 - maxVal;

    clusterNums = zeros(k, 1);
    for i = 1001: 2000
        label = clusterLabels(i);
        clusterNums(label) = clusterNums(label) + 1;
    end
    [maxVal, maxIdx] = max(clusterNums);
    error = error + 1000 - maxVal;
    error = error * 1.0 / 2000
end
```

Code for single-linkage clustering:

```
load('test79.mat');
testData = d79;

distMat = pdist(testData);
Z = linkage(distMat, 'single');
% dendrogram(Z)

ks = [2, 5, 10, 50];
for kIdx = 1: size(ks, 2)
    error = 0;
    k = ks(kIdx);
    clusterLabels = cluster(Z,'maxclust', k) ;

    clusterNums = zeros(k, 1);
    for i = 1: 1000
```

```
        label = clusterLabels(i);
        clusterNums(label) = clusterNums(label) + 1;
    end
    [maxVal, maxIdx] = max(clusterNums);
    error = 1000 - maxVal;

    clusterNums = zeros(k, 1);
    for i = 1001: 2000
        label = clusterLabels(i);
        clusterNums(label) = clusterNums(label) + 1;
    end
    [maxVal, maxIdx] = max(clusterNums);
    error = error + 1000 - maxVal;
    error = error * 1.0 / 2000
end
```