# EE583 Pattern Recognition HW5

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# 1 Question 1

3 different experiments are conducted. In each experiment, ten models are individually used to calculate the accuracy, or equivalently misclassification loss.

### 1.1 Default settings

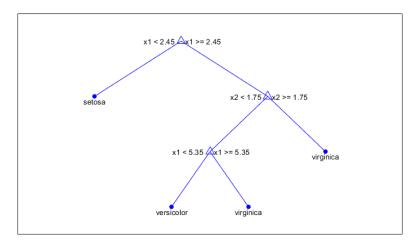


Figure 1: Visualization of the first tree

This 3 split tree resulted in a loss of 0.0267.

### 1.2 Maximum number of Splits Restriction

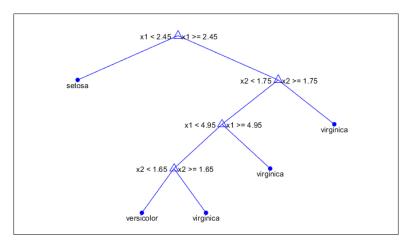


Figure 2: Visualization of the second tree

For this experiment the resultant number of splits was higher than the first one. Therefore, it resulted in less misclassification loss of 0.0240.

### 1.3 Maximum number of Splits Restriction

Changing the split criterion from Gini's diversity index to deviance resulted in the improvement of the accuracy.

# 2 Question 2

### 2.1 Single tree vs Ensemble

To observe the performance difference between a single tree and the ensemble better, the number of splits were set to 1 to decrease the classification capability of the single tree. Otherwise, even the first week learner is able to classify the data accurate enough.

$$Accuracy_{first} = 0.64$$
  $Accuracy_{ensemble} = 0.95$ 

The results reflect our expectations on the performance of the ensemble trained with Adaboost being better.

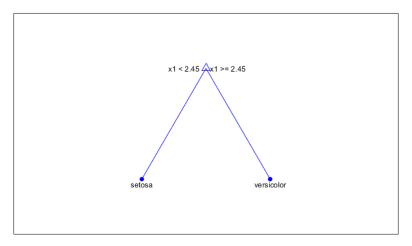


Figure 3: Visualization of the first tree

#### 2.2 Learning Rate

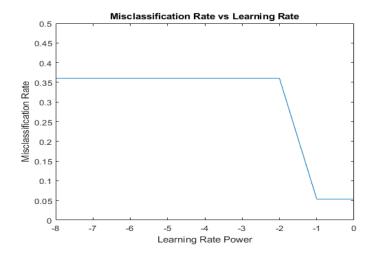


Figure 4: Learning Rate vs Misclassification

Again, the maximum number of splits is fixed among experiments, which can be seen in 5.2. Larger learning rates resulted ensemble to achieve higher accuracy, since the informative samples have more weights in the training process.

# 3 Question 3

### 3.1 Learning Rate

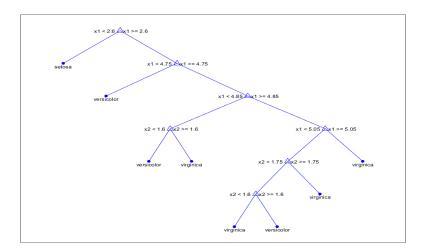


Figure 5: First Tree

The accuracy of the first tree is calculated as 0.9867 whereas the forest's is 1. We see that, with the help of the 24 remaining tree models in the tree-bagger object, the model was able to classify the samples correctly that are misclassified by the first tree. Hence, the classification accuracy improved.

# 4 Question 4

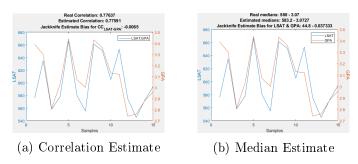


Figure 6: Jackknife estimates

The variables are plotted with respect to different axes in both Figure 6a and 6b. The estimates and the estimated bias are calculated and printed in the title. The resultant biases are respectively low when the variance of the relative variables are taken into account.

### 5 APPENDIX

The code given in this section is shared @**Q**.

#### 5.1 Q1

```
%%
2 clear; clc;
  chdir('...')
  addpath ('export_fig')
  chdir ('HW5')
  rng (101)
  %%
  load fisheriris.mat
  feats = meas(:, 3:4);
  Y = species;
11
  tree_model = fitctree (feats, species, 'CrossVal', 'on');
12
   view (tree_model.Trained {1}, 'Mode', 'graph')
  Ls = [];
  \begin{array}{cccc} \textbf{for} & i & = & 1:10 \end{array}
15
       model = tree_model.Trained{i};
16
       preds = predict(model, feats);
17
       confusion matrix = confusionmat (species, preds);
18
       accuracy = sum(diag(confusion matrix))/sum(sum(confusion matrix))
19
       loss = 1 - accuracy;
20
       Ls(end+1) = loss;
21
  end
22
  mean loss default = mean(Ls);
^{23}
24
  %%
25
  tree_model = fitctree (feats, species, 'CrossVal', 'on', 'MaxNumSplits',7)
26
   view (tree model. Trained {1}, 'Mode', 'graph')
27
  Ls = [];
28
  for i = 1:10
29
       model = tree model.Trained{i};
30
       preds = predict(model, feats);
31
       confusion matrix = confusionmat (species, preds);
32
       accuracy = sum(diag(confusion matrix))/sum(sum(confusion matrix))
33
       loss = 1 - accuracy;
34
       Ls(end+1) = loss;
35
36
  mean_loss_restricted_splits = mean(Ls);
37
  %%
38
  tree_model = fitctree (feats, species, 'CrossVal', 'on', 'SplitCriterion',
      'deviance');
  view (tree model. Trained {1}, 'Mode', 'graph')
  Ls = |\cdot|;
41
  for i = 1:10
```

```
model = tree model.Trained{i};
43
       preds = predict(model, feats);
44
       confusion matrix = confusionmat (species, preds);
45
       accuracy = sum (diag (confusion_matrix))/sum (sum (confusion_matrix))
^{46}
       loss = 1 - accuracy;
47
       Ls(end+1) = loss;
48
49
  mean_loss_split_criterion = mean(Ls);
50
  figHandles = findall(0, 'Type', 'figure');
52
53
  for i = 1:numel(figHandles)
54
       export_fig(['Q1_',num2str(i)], '-png', figHandles(i), '-append')
55
  end
56
57
  hTree=findall(0, 'Tag', 'tree viewer');
  % close (hTree)
59
60
  mean loss default
61
  mean\_loss\_restricted\_splits
62
  mean loss split criterion
```

### 5.2 Q2

```
1 clc, clear;
2 load fisheriris.mat
  feats = meas(:,3:4);
 Y = species;
  rng(101)
5
  % Cross varidation (train: 50%, test: 50%)
  cv = cvpartition(size(feats,1),'HoldOut',0.5);
  idx = cv.test;
9
10
  % Separate to training and test data
11
  feats Train = feats(~idx,:);
  feats Test = feats(idx,:);
  Y \text{ Train} = Y(\tilde{idx});
14
  Y_Test = Y(idx);
15
16
  % To amplify the difference of the classification success, the number
17
       o f
  % splits are restricted for a single tree to also highlight the
      adaboost
  % success
19
  t = templateTree('MaxNumSplits',1);
20
  Mdl = fitcensemble (feats_Train, Y_Train, 'Method', 'AdaBoostM2', ...
21
       'Learners',t,'NumLearningCycles',25);
22
  view (Mdl. Trained {1}, 'Mode', 'graph')
23
  preds = predict (Mdl. Trained {1}, feats Test);
24
  confusionmatrix = confusionmat(Y_Test, preds);
25
  first\_tree\_accuracy = sum(diag(confusionmatrix))/sum(sum(
26
      confusion matrix))
  preds = predict (Mdl, feats Test);
  confusionmatrix = confusionmat(Y_Test, preds);
  ensemble_tree_accuracy = sum(diag(confusionmatrix))/sum(sum(
29
      confusion matrix))
30
31
  accs = [];
32
  for lr = 10.^{-1} - 8:0
33
       t = templateTree('MaxNumSplits',3);
34
       Mdl = fitcensemble (feats_Train, Y_Train, 'Method', 'AdaBoostM2', ...
35
       'Learners', t, 'NumLearningCycles', 25, 'LearnRate', lr);
36
       preds = predict(Mdl, feats_Test);
37
       confusionmatrix = confusionmat(Y Test, preds);
38
       model\_accuracy = sum(diag(confusionmatrix))/sum(sum(
39
          confusionmatrix));
       accs (end+1) = model_accuracy;
40
  end
41
42
  figure
43
  plot(-8:0,1-accs)
```

```
45 ylim([0 0.5])
46 title('Misclassification Rate vs Learning Rate')
47 ylabel('Misclassification Rate')
48 xlabel('Learning Rate Power')
```

#### 5.3 Q3

```
1 clc, clear;
2 load fisheriris.mat
  feats = meas(:, 3:4);
_{4} Y = species;
  rng (101)
  % Cross varidation (train: 50%, test: 50%)
  cv = cvpartition(size(feats,1),'HoldOut',0.5);
  idx = cv.test;
9
10
  % Separate to training and test data
11
  feats Train = feats(~idx,:);
  feats Test = feats(idx,:);
  Y \text{ Train} = Y(\tilde{idx});
14
  Y_Test = Y(idx);
15
16
  Mdl = TreeBagger (25, feats, Y, 'OOBPrediction', 'On', ...
17
       'Method', 'classification', 'SampleWithReplacement', 'on');
18
19
20
  view (Mdl. Trees {1}, 'Mode', 'graph')
21
  preds = predict(Mdl.Trees{1},feats_Test);
22
  confusionmatrix = confusionmat(Y Test, preds);
23
  first tree accuracy = sum(diag(confusionmatrix))/sum(sum(
24
      confusion matrix))
  preds = predict(Mdl, feats Test);
^{25}
  confusionmatrix = confusionmat(Y_Test, preds);
  ensemble\_tree\_accuracy = sum(diag(confusionmatrix))/sum(sum(
      confusionmatrix))
```

#### 5.4 Q4

```
1 load lawdata
  rhohat = corr(lsat,gpa);
3
  %%
4
  rng default; % For reproducibility
  jackrho = jackknife(@corr,lsat,gpa);
  meanrho = mean(jackrho);
  yyaxis left
  plot (lsat)
9
  ylabel ('LSAT')
10
  hold on
11
  yyaxis right
  plot (gpa)
  h = ylabel ('GPA', 'Rotation', 270);
14
  xlabel ('Samples')
15
  h. Position (1) = 16.5; % change horizontal position of ylabel
16
  legend ('LSAT,GPA')
17
  n = length(lsat);
  biasrho = round((n-1) * (meanrho-rhohat), 4);
19
   title ({['Real Correlation: ',num2str(rhohat)],['Estimated Correlation
         , num2str(meanrho)]},['Jackknife Estimate Bias for CC_{LSAT-GPA
         ', num2str(biasrho)], 'FontWeight', 'bold')
21
22
23
  %%
24
  rng default; % For reproducibility
25
  jackmed = jackknife (@median, lsat);
26
  meanmed lsat = mean(jackmed);
27
  n = length(lsat);
  bias_lsat_median = (n-1) * (meanmed_lsat-median(lsat))
29
30
  jackmed = jackknife(@median,gpa);
31
  meanmed gpa = mean(jackmed);
32
  n = length(gpa);
33
  bias gpa median = (n-1) * (meanmed gpa-median (gpa))
34
35
  figure
36
  yyaxis left
37
  hp1 = plot(lsat);
38
  ylabel ('LSAT')
39
  hold on
  yyaxis right
41
  hp2 = plot(gpa);
  legend ([hp1,hp2], 'LSAT', 'GPA')
  xlabel('Samples')
44
  h = ylabel ('GPA', 'Rotation', 270);
  h. Position (1) = 16.5; % change horizontal position of ylabel
47
```

```
title ({['Real medians: ',num2str(median(lsat)),' - ',num2str(median(
     gpa))],['Estimated medians: ',num2str(meanmed_lsat),' - ',num2str(
     meanmed_gpa)],['Jackknife Estimate Bias for LSAT & GPA: ',num2str(
     bias_lsat_median), '- ', num2str(bias_gpa_median)]})
49
50
51
  figHandles = findall(0, 'Type', 'figure');
52
53
  for i = 1:numel(figHandles)
      export_fig(['Q4_',num2str(i)], '-png', figHandles(i), '-append')
55
  end
56
  close all
```