

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

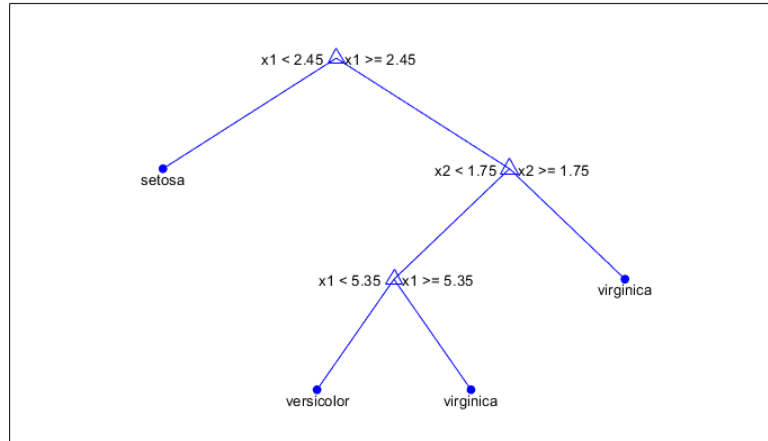


Figure 1: Visualization of the first tree

This 3 split tree resulted in a loss of 0.0267.

1.2 Maximum number of Splits Restriction

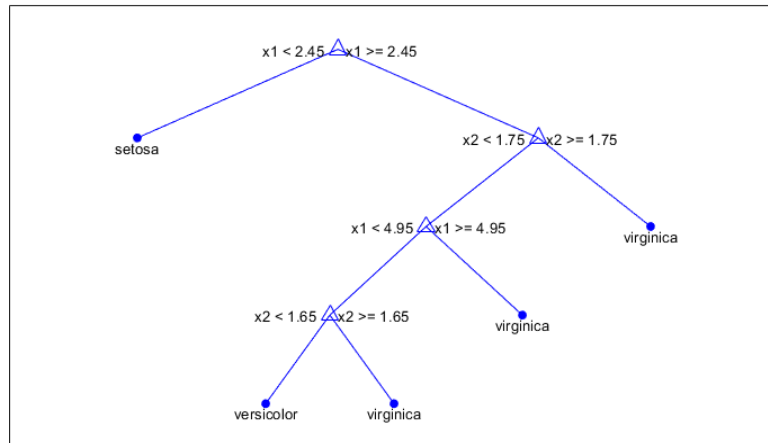


Figure 2: Visualization of the second tree

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

3 Question 3

4 Question 4

5 APPENDIX

The code given in this section is shared @.

5.1 Q1

```

1 %%
2 clear; clc;
3 chdir('..')
4 addpath('export_fig')
5 chdir('HW5')
6 rng(101)
7 %%
8 load fisheriris.mat
9 feats = meas(:,3:4);
10 Y = species;
11 %%
12 tree_model = fitctree(feats,species,'CrossVal','on');
13 view(tree_model.Trained{1},'Mode','graph')
14 Ls = [];
15 for i = 1:10
16     model = tree_model.Trained{i};
17     preds = predict(model,feats);
18     confusion_matrix = confusionmat(species,preds);
19     accuracy = sum(diag(confusion_matrix))/sum(sum(confusion_matrix))
20     ;
21     loss = 1 - accuracy;
22     Ls(end+1) = loss;
23 end
24 mean_loss_default = mean(Ls);
25 %%
26 tree_model = fitctree(feats,species,'CrossVal','on','MaxNumSplits',7)
27 ;
28 view(tree_model.Trained{1},'Mode','graph')
29 Ls = [];
30 for i = 1:10
31     model = tree_model.Trained{i};
32     preds = predict(model,feats);
33     confusion_matrix = confusionmat(species,preds);
34     accuracy = sum(diag(confusion_matrix))/sum(sum(confusion_matrix))
35     ;
36     loss = 1 - accuracy;
37     Ls(end+1) = loss;
38 end
39 mean_loss_restricted_splits = mean(Ls);
40 %%
41 tree_model = fitctree(feats,species,'CrossVal','on','SplitCriterion','deviance');
42 view(tree_model.Trained{1},'Mode','graph')
43 Ls = [];
44 for i = 1:10

```

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

5.2 Q2

```

1  clc , clear ;
2  load fisheriris.mat
3  feats = meas(:,3:4);
4  Y = species;
5  rng(101)
6
7  % Cross varidation (train: 50%, test: 50%)
8  cv = cvpartition(size(feats,1), 'HoldOut', 0.5);
9  idx = cv.test;
10
11 % Separate to training and test data
12 feats_Train = feats(~idx,:);
13 feats_Test = feats(idx,:);
14 Y_Train = Y(~idx);
15 Y_Test = Y(idx);
16
17 % To amplify the difference of the classification success , the number
    of
18 % splits are restricted for a single tree to also highlight the
    adaboost
19 % success
20 t = templateTree('MaxNumSplits',1);
21 Mdl = fitcensemble(feats_Train,Y_Train,'Method','AdaBoostM2', ...
22     'Learners',t,'NumLearningCycles',25);
23 view(Mdl.Trained{1},'Mode','graph')
24 preds = predict(Mdl.Trained{1},feats_Test);
25 confusionmatrix = confusionmat(Y_Test,preds);
26 first_tree_accuracy = sum(diag(confusionmatrix))/sum(sum(
    confusionmatrix))
27 preds = predict(Mdl,feats_Test);
28 confusionmatrix = confusionmat(Y_Test,preds);
29 ensemble_tree_accuracy = sum(diag(confusionmatrix))/sum(sum(
    confusionmatrix))
30
31
32
33 accs = [];
34 for lr = 10.^[-8:0]
35     t = templateTree('MaxNumSplits',1);
36     Mdl = fitcensemble(feats_Train,Y_Train,'Method','AdaBoostM2', ...
37         'Learners',t,'NumLearningCycles',25, 'LearnRate',lr);
38     preds = predict(Mdl,feats_Test);
39     confusionmatrix = confusionmat(Y_Test,preds);
40     model_accuracy = sum(diag(confusionmatrix))/sum(sum(
        confusionmatrix));
41     accs(end+1) = model_accuracy;
42 end
43
44 figure

```

```
45 plot(-8:0,1-accs)
46 ylim([0 0.5])
47 title('Misclassification Rate vs Learning Rate')
48 ylabel('Misclassification Rate')
49 xlabel('Learning Rate Power')
```

5.3 Q3

```
1  clc , clear ;
2  load fisheriris.mat
3  feats = meas(:,3:4);
4  Y = species;
5  rng(101)
6
7  % Cross varidation (train: 50%, test: 50%)
8  cv = cvpartition(size(feats,1), 'HoldOut', 0.5);
9  idx = cv.test;
10
11 % Separate to training and test data
12 feats_Train = feats(~idx,:);
13 feats_Test = feats(idx,:);
14 Y_Train = Y(~idx);
15 Y_Test = Y(idx);
16
17 Mdl = TreeBagger(25, feats, Y, 'OOBPrediction', 'On', ...
18     'Method', 'classification', 'SampleWithReplacement', 'on');
19
20
21 view(Mdl.Trees{1}, 'Mode', 'graph')
22 preds = predict(Mdl.Trees{1}, feats_Test);
23 confusionmatrix = confusionmat(Y_Test, preds);
24 first_tree_accuracy = sum(diag(confusionmatrix))/sum(sum(
    confusionmatrix))
25 preds = predict(Mdl, feats_Test);
26 confusionmatrix = confusionmat(Y_Test, preds);
27 ensemble_tree_accuracy = sum(diag(confusionmatrix))/sum(sum(
    confusionmatrix))
```


5.4 Q4

```

1 load lawdata
2 rhohat = corr(lsat , gpa);
3
4 %%
5 rng default; % For reproducibility
6 jackrho = jackknife(@corr, lsat , gpa);
7 meanrho = mean(jackrho);
8 yyaxis left
9 plot(lsat)
10 ylabel('LSAT')
11 hold on
12 yyaxis right
13 plot(gpa)
14 h = ylabel('GPA', 'Rotation', 270);
15 xlabel('Samples')
16 h.Position(1) = 16.5; % change horizontal position of ylabel
17 legend('LSAT', 'GPA')
18 title(['Real Correlation: ', num2str(rhohat)], ['Estimated Correlation'
        : ', ', num2str(meanrho)]])
19
20 n = length(lsat);
21 biasrho = (n-1) * (meanrho-rhohat)
22
23
24 %%
25 rng default; % For reproducibility
26 jackmed = jackknife(@median, lsat);
27 meanmed_lsat = mean(jackmed);
28 n = length(lsat);
29 bias_lsat_median = (n-1) * (meanmed_lsat-median(lsat))
30
31 jackmed = jackknife(@median, gpa);
32 meanmed_gpa = mean(jackmed);
33 figure
34 yyaxis left
35 hp1 = plot(lsat);
36 ylabel('LSAT')
37 hold on
38 yyaxis right
39 hp2 = plot(gpa);
40 legend([hp1, hp2], 'LSAT', 'GPA')
41 xlabel('Samples')
42 h = ylabel('GPA', 'Rotation', 270);
43 h.Position(1) = 16.5; % change horizontal position of ylabel
44 n = length(gpa);
45 bias_gpa_median = (n-1) * (meanmed_gpa-median(gpa))
46 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_gpa_median), ' - ', num2str(bias_gpa_median) ]})  
47  
48  
49  
50 figHandles = findall(0, 'Type', 'figure');  
51  
52 for i = 1:numel(figHandles)  
53     export_fig([ 'Q4_', num2str(i) ], '-png', figHandles(i), '-append')  
54 end
```