```
% Gini classificaton tree with carseats

T = readtable('Carseats_train.csv')

% need to create high variable and attach it to the table

T{T.Sales < 8, "High" } = 0
T{T.Sales >= 8, "High" } = 1


%Delete Sales and Index column

T= removevars(T,{'Sales'});
T= removevars(T,{'Var1'});

%fitting classification tree with gini (default)

tc = fitctree(T, "High", "MinLeafSize", 5, "MinParentSize",
 10, "MergeLeaves", "off")

%View tree
%view(tc,'Mode','graph')
view(tc,'Mode','text')


%looks good, can save the graph
%need to see if i can get tabular output


%prediction
test = readtable('Carseats_test.csv')

test{test.Sales < 8, "High" } = 0
test{test.Sales >= 8, "High" } = 1

y_test = test.High
test= removevars(test,{'Var1'});
test= removevars(test,{'High'});
test= removevars(test,{'Sales'});


test_pred = predict(tc, test)
test_results = table(y_test, test_pred)

y_train = T.High
train= removevars(T,{'High'});

missclass = 0
for i = 1:length(y_test)
    if test_results.y_test(i) ~= test_results.test_pred(i)
        missclass = missclass +1
    end
```

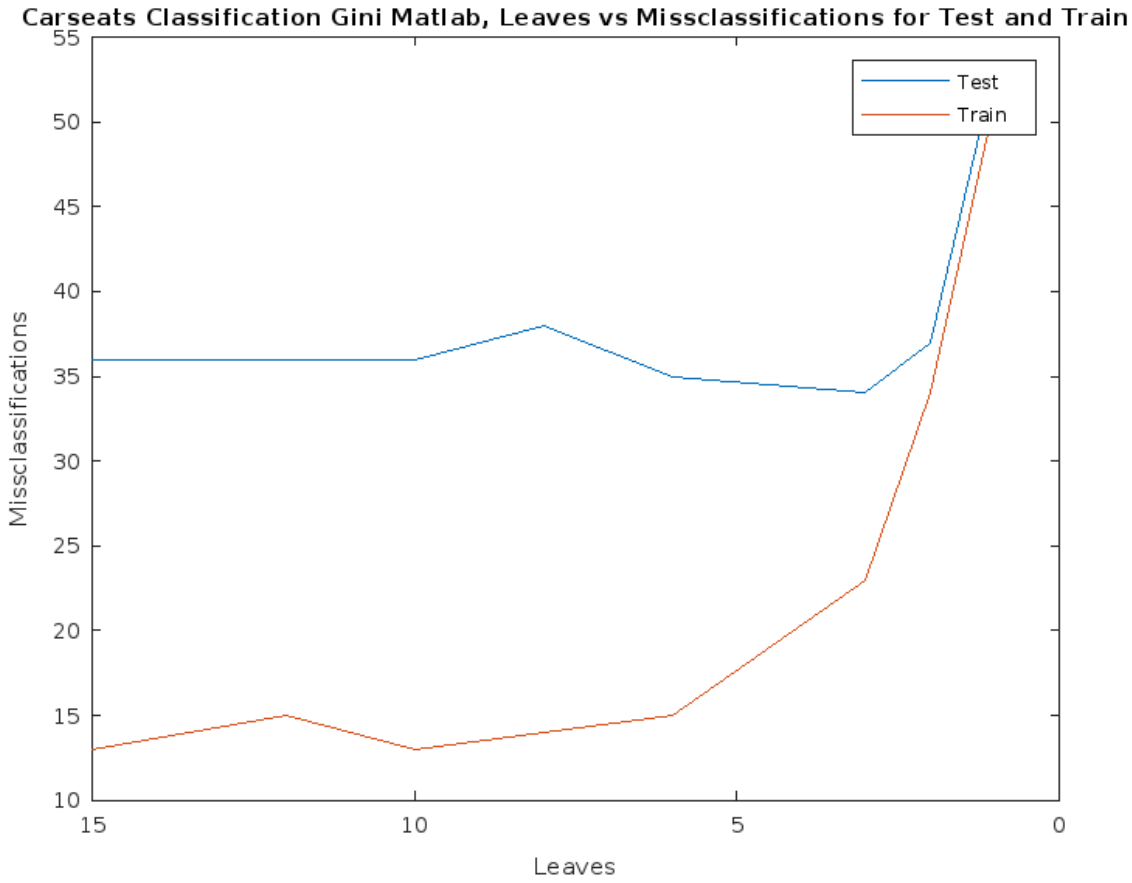
```
end


%misclassifications

miss_test = []
miss_train = []
leaves = []
for i = 1:max(tc.PruneList)
    ptc = prune(tc, "level", i )
    test_pred = predict(ptc, test)
    test_results = table(y_test, test_pred)
    leaves = [leaves sum(~ptc.IsBranchNode)]
    missclass = 0
    for i = 1:length(y_test)
        if test_results.y_test(i) ~= test_results.test_pred(i)
            missclass = missclass +1
        end
    end


    miss_test = [miss_test missclass]

    train_pred = predict(ptc, train)
    train_results = table(y_train, train_pred)

    missclass = 0
    for i = 1:length(y_test)
        if train_results.y_train(i) ~= train_results.train_pred(i)
            missclass = missclass +1
        end
    end
    miss_train = [miss_train missclass]

end


figure
plot(leaves, miss_test, leaves, miss_train)
title('Carseats Classification Gini Matlab, Leaves vs Missclassifications for
 Test and Train')
xlabel('Leaves')
ylabel('Missclassifications')
legend('Test','Train')

ax = gca
ax.XDir = "reverse"



ptc = prune(tc, "level", 6 ) %max level (15) - min mse level (3) +1
view(ptc,'Mode','graph')
```

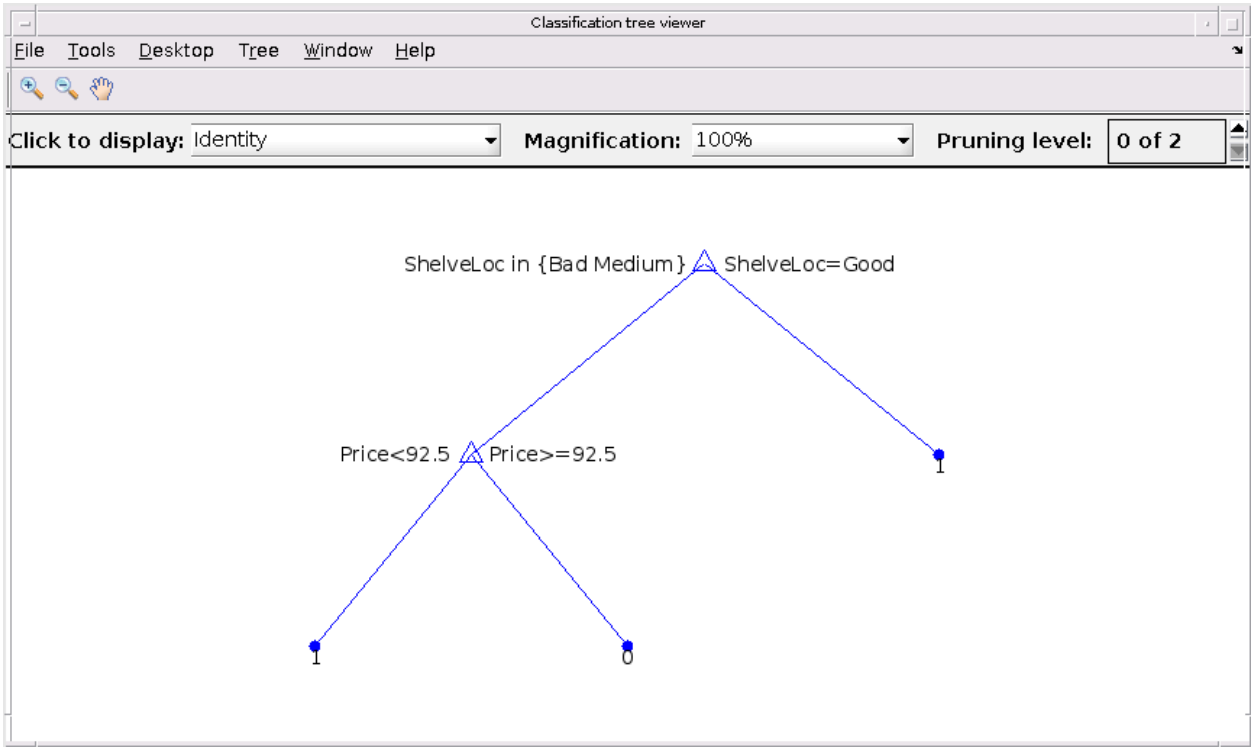
```
test_pred = predict(ptc, test)
test_results = table(y_test, test_pred)

missclass = 0
for i = 1:length(y_test)
    if test_results.y_test(i) ~= test_results.test_pred(i)
        missclass = missclass +1
    end
end
missclass


T =

  280x12 table

    Var1    Sales    CompPrice    Income    Advertising    Population    Price
    ShelveLoc     Age    Education     Urban       US
    ____    _____    _________    ______    ___________    __________    _____
    __________    ___    _________    _______    _______

      1       9.5       138          73          11            276         120
    {'Bad'   }    42        17         {'Yes'}    {'Yes'}
      2     11.22       111          48          16            260          83
    {'Good'  }    65        10         {'Yes'}    {'Yes'}
      3     10.06       113          35          10            269          80
    {'Medium'}    59        12         {'Yes'}    {'Yes'}
      4       7.4       117         100           4            466          97
    {'Medium'}    55        14         {'Yes'}    {'Yes'}
      5      4.15       141          64           3            340         128
    {'Bad'   }    38        13         {'Yes'}    {'No' }
      6     10.81       124         113          13            501          72
    {'Bad'   }    78        16         {'No' }    {'Yes'}
      7      6.63       115         105           0             45         108
    {'Medium'}    71        15         {'Yes'}    {'No' }
      8     11.85       136          81          15            425         120
    {'Good'  }    67        10         {'Yes'}    {'Yes'}
      9      6.54       132         110           0            108         124
    {'Medium'}    76        10         {'No' }    {'No' }
     10      4.69       132         113           0            131         124
    {'Medium'}    76        17         {'No' }    {'Yes'}
     11      9.01       121          78           9            150         100
    {'Bad'   }    26        10         {'No' }    {'Yes'}
     12     11.96       117          94           4            503          94
    {'Good'  }    50        13         {'Yes'}    {'Yes'}
     13      3.98       122          35           2            393         136
    {'Medium'}    62        18         {'Yes'}    {'No' }
     14     10.96       115          28          11             29          86
    {'Good'  }    53        18         {'Yes'}    {'Yes'}
     15     11.17       107         117          11            148         118
    {'Good'  }    52        18         {'Yes'}    {'Yes'}
     16      8.71       149          95           5            400         144
    {'Medium'}    76        18         {'No' }    {'No' }
```

17	7.58	118	32	0	284	110	{'Good' }	63	13	{'Yes'}	{'No' }
18	12.29	147	74	13	251	131	{'Good' }	52	10	{'Yes'}	{'Yes'}
19	13.91	110	110	0	408	68	{'Good' }	46	17	{'No' }	{'Yes'}
20	8.73	129	76	16	58	121	{'Medium'}	69	12	{'Yes'}	{'Yes'}
21	6.41	125	90	2	367	131	{'Medium'}	35	18	{'Yes'}	{'Yes'}
22	12.13	134	29	12	239	109	{'Good' }	62	18	{'No' }	{'Yes'}
23	5.08	128	46	6	497	138	{'Medium'}	42	13	{'Yes'}	{'No' }
24	5.87	121	31	0	292	109	{'Medium'}	79	10	{'Yes'}	{'No' }
25	10.14	145	119	16	294	113	{'Bad' }	42	12	{'Yes'}	{'Yes'}
26	14.9	139	32	0	176	82	{'Good' }	54	11	{'No' }	{'No' }
27	8.33	107	115	11	496	131	{'Good' }	50	11	{'No' }	{'Yes'}
28	5.27	98	118	0	19	107	{'Medium'}	64	17	{'Yes'}	{'No' }
29	2.99	103	74	0	359	97	{'Bad' }	55	11	{'Yes'}	{'Yes'}
30	7.81	104	99	15	226	102	{'Bad' }	58	17	{'Yes'}	{'Yes'}
31	13.55	125	94	0	447	89	{'Good' }	30	12	{'Yes'}	{'No' }
32	8.25	136	58	16	241	131	{'Medium'}	44	18	{'Yes'}	{'Yes'}
33	6.2	107	32	12	236	137	{'Good' }	64	10	{'No' }	{'Yes'}
34	8.77	114	38	13	317	128	{'Good' }	50	16	{'Yes'}	{'Yes'}
35	2.67	115	54	0	406	128	{'Medium'}	42	17	{'Yes'}	{'Yes'}
36	11.07	131	84	11	29	96	{'Medium'}	44	17	{'No' }	{'Yes'}
37	8.89	122	76	0	270	100	{'Good' }	60	18	{'No' }	{'No' }
38	4.95	121	41	5	412	110	{'Medium'}	54	10	{'Yes'}	{'Yes'}
39	6.59	109	73	0	454	102	{'Medium'}	65	15	{'Yes'}	{'No' }
40	3.24	130	60	0	144	138	{'Bad' }	38	10	{'No' }	{'No' }
41	2.07	119	98	0	18	126	{'Bad' }	73	17	{'No' }	{'No' }
42	7.96	157	53	0	403	124	{'Bad' }	58	16	{'Yes'}	{'No' }
43	10.43	77	69	0	25	24	{'Medium'}	50	18	{'Yes'}	{'No' }

```
 44      4.12        123          42          11           16          134
{'Medium'}    59         13        {'Yes'}    {'Yes'}
 45      4.16         85          79           6          325          95
{'Medium'}    69         13        {'Yes'}    {'Yes'}
 46      4.56        141          63           0          168         135
{'Bad'   }    44         12        {'Yes'}    {'Yes'}
 47     12.44        127          90          14           16          70
{'Medium'}    48         15        {'No' }    {'Yes'}
 48      4.38        126          98           0          173         108
{'Bad'   }    55         16        {'Yes'}    {'No' }
 49      3.91        116          52           0          349          98
{'Bad'   }    69         18        {'Yes'}    {'No' }
 50     10.61        157          93           0           51         149
{'Good'  }    32         17        {'Yes'}    {'No' }
 51      1.42         99          32          18          341         108
{'Bad'   }    80         16        {'Yes'}    {'Yes'}
 52      4.42        121          90           0          150         108
{'Bad'   }    75         16        {'Yes'}    {'No' }
 53      7.91        153          40           3          112         129
{'Bad'   }    39         18        {'Yes'}    {'Yes'}
 54      6.92        109          64          13           39         119
{'Medium'}    61         17        {'Yes'}    {'Yes'}
 55       4.9        134         103          13           25         144
{'Medium'}    76         17        {'No' }    {'Yes'}
 56      6.85        143          81           5           60         154
{'Medium'}    61         18        {'Yes'}    {'Yes'}
 57     11.91        133          82           0           54          84
{'Medium'}    50         17        {'Yes'}    {'No' }
 58      0.91         93          91           0           22         117
{'Bad'   }    75         11        {'Yes'}    {'No' }
 59      5.42        103          93          15          188         103
{'Bad'   }    74         16        {'Yes'}    {'Yes'}
 60      5.21        118          71           4          148         114
{'Medium'}    80         13        {'Yes'}    {'No' }
 61      8.32        122         102          19          469         123
{'Bad'   }    29         13        {'Yes'}    {'Yes'}
 62      7.32        105          32           0          358         107
{'Medium'}    26         13        {'No' }    {'No' }
 63      1.82        139          45           0          146         133
{'Bad'   }    77         17        {'Yes'}    {'Yes'}
 64      8.47        119          88          10          170         101
{'Medium'}    61         13        {'Yes'}    {'Yes'}
 65       7.8        100          67          12          184         104
{'Medium'}    32         16        {'No' }    {'Yes'}
 66       4.9        122          26           0          197         128
{'Medium'}    55         13        {'No' }    {'No' }
 67      8.85        127          92           0          508          91
{'Medium'}    56         18        {'Yes'}    {'No' }
 68      9.01        126          61          14          152         115
{'Medium'}    47         16        {'Yes'}    {'Yes'}
 69     13.39        149          69          20          366         134
{'Good'  }    60         13        {'Yes'}    {'Yes'}
 70      7.99        127          59           0          339          99
{'Medium'}    65         12        {'Yes'}    {'No' }
```

```
 71      9.46         89          81           15           237           99
{'Good'  }    74         12        {'Yes'}     {'Yes'}
 72       6.5        148          51           16           148          150
{'Medium'}    58         17        {'No' }     {'Yes'}
 73      5.52        115          45            0           432          116
{'Medium'}    25         15        {'Yes'}     {'No' }
 74     12.61        118          90           10            54          104
{'Good'  }    31         11        {'No' }     {'Yes'}
 75       6.2        150          68            5           125          136
{'Medium'}    64         13        {'No' }     {'Yes'}
 76      8.55         88         111           23           480           92
{'Bad'   }    36         16        {'No' }     {'Yes'}
 77     10.64        102          87           10           346           70
{'Medium'}    64         15        {'Yes'}     {'Yes'}
 78       7.7        118          71           12            44           89
{'Medium'}    67         18        {'No' }     {'Yes'}
 79      4.43        134          48            1           139          145
{'Medium'}    65         12        {'Yes'}     {'Yes'}
 80      9.14        134          67            0           286           90
{'Bad'   }    41         13        {'Yes'}     {'No' }
 81      8.01        113         100           16           353           79
{'Bad'   }    68         11        {'Yes'}     {'Yes'}
 82      7.52        116          72            0           237          128
{'Good'  }    70         13        {'Yes'}     {'No' }
 83     11.62        151          83            4           325          139
{'Good'  }    28         17        {'Yes'}     {'Yes'}
 84      4.42        109          36            7           468           94
{'Bad'   }    56         11        {'Yes'}     {'Yes'}
 85      2.23        111          25            0            52          121
{'Bad'   }    43         18        {'No' }     {'No' }
 86      8.47        125         103            0           304          112
{'Medium'}    49         13        {'No' }     {'No' }
 87       8.7        150          84            9           432          134
{'Medium'}    64         15        {'Yes'}     {'No' }
 88      11.7        131          67            7           272          126
{'Good'  }    54         16        {'No' }     {'Yes'}
 89      6.56        117          42            7           144          111
{'Medium'}    62         10        {'Yes'}     {'Yes'}
 90      7.95        128          66            3           493          119
{'Medium'}    45         16        {'No' }     {'No' }
 91      5.33        115          22            0           491          103
{'Medium'}    64         11        {'No' }     {'No' }
 92      4.81         97          46           11           267          107
{'Medium'}    80         15        {'Yes'}     {'Yes'}
...
```


Carseats Classification Gini Matlab, Leaves vs Missclassifications for Test and Train
Test
Train
Missclassifications
Leaves
55
50
45
40
35
30
25
20
15
10
15
10
5
0


Classification tree viewer
File Tools Desktop Tree Window Help
Click to display: Identity
Magnification: 100%
Pruning level: 0 of 2
ShelveLoc in {Bad Medium}
ShelveLoc=Good
Price<92.5
Price>=92.5
1
1
0

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