```
% 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 = fitrtree(T, "Price", "MinLeafSize", 5, "MinParentSize",
 10, "MergeLeaves", "off")
%maxdepth wont work as it needs a tall array


%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

%preduction
test = readtable('Carseats_test.csv')
test= removevars(test,{'Var1'});
y_test = test.Price
test= removevars(test,{'Price'});

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

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

%mse

sum((test_results.y_test - test_results.test_pred).^2)/length(y_test)

%need to figure out how to do pruned tree, but first prediction
%ptc = prune(tc)
%view(ptc,'Mode','graph')

%need to get mse for each prune level
%ptc.PruneList
```

```
%ptc.Prunealpha
%max(tc.PruneList)

mse_test = []
mse_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)]
    %sum(~ptc.IsBranchNode)
    %ptc.NumNodes - sum(ptc.IsBranchNode)
    mse_test = [mse_test sum((test_results.y_test -
 test_results.test_pred).^2)/length(y_test)]

    train_pred = predict(ptc, train)
    train_results = table(y_train, train_pred)
    mse_train = [mse_train sum((train_results.y_train -
 train_results.train_pred).^2)/length(y_train)]

end
%parenthesis for indexing
%min is 29 leaves from invesigating graph

%plot the result

figure
plot(leaves, mse_test, leaves, mse_train)
title('Carseats Regression Matlab, Leaves vs MSE for Test')
xlabel('Leaves')
ylabel('MSE')
ax = gca
ax.XDir = "reverse"

ptc = prune(tc, "level", 15 ) %max level (43) - min mse level (29) +1
test_pred = predict(ptc, test)
test_results = table(y_test, test_pred)
sum((test_results.y_test - test_results.test_pred).^2)/length(y_test)

view(ptc,'Mode','graph')
view(ptc,'Mode','text')
```

T =

280x12 table

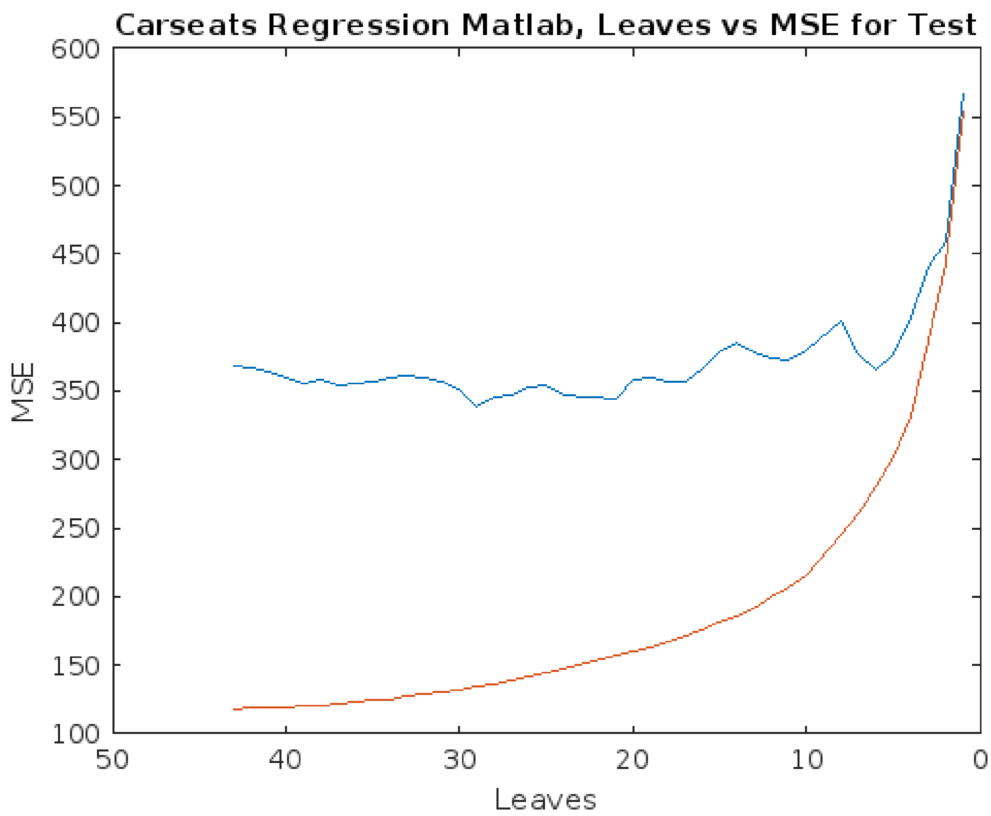
Var1	*Sales*	*CompPrice*	*Income*	*Advertising*	*Population*	*Price*	*ShelveLoc*	*Age*	*Education*	*Urban*	*US*

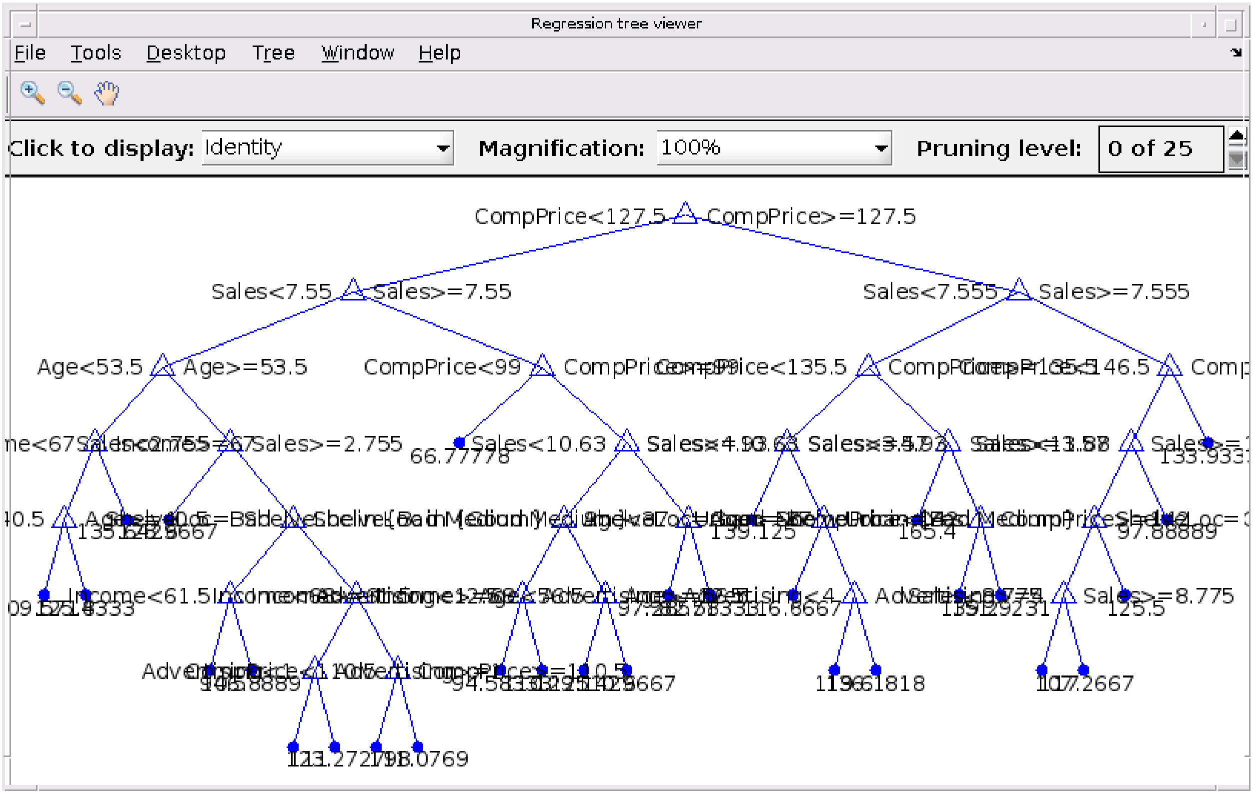
1	9.5	138	73	11	276	120	{'Bad' }	42	17	{'Yes'}	{'Yes'}
2	11.22	111	48	16	260	83	{'Good' }	65	10	{'Yes'}	{'Yes'}
3	10.06	113	35	10	269	80	{'Medium'}	59	12	{'Yes'}	{'Yes'}
4	7.4	117	100	4	466	97	{'Medium'}	55	14	{'Yes'}	{'Yes'}
5	4.15	141	64	3	340	128	{'Bad' }	38	13	{'Yes'}	{'No' }
6	10.81	124	113	13	501	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'}
...
```





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