Lab 7

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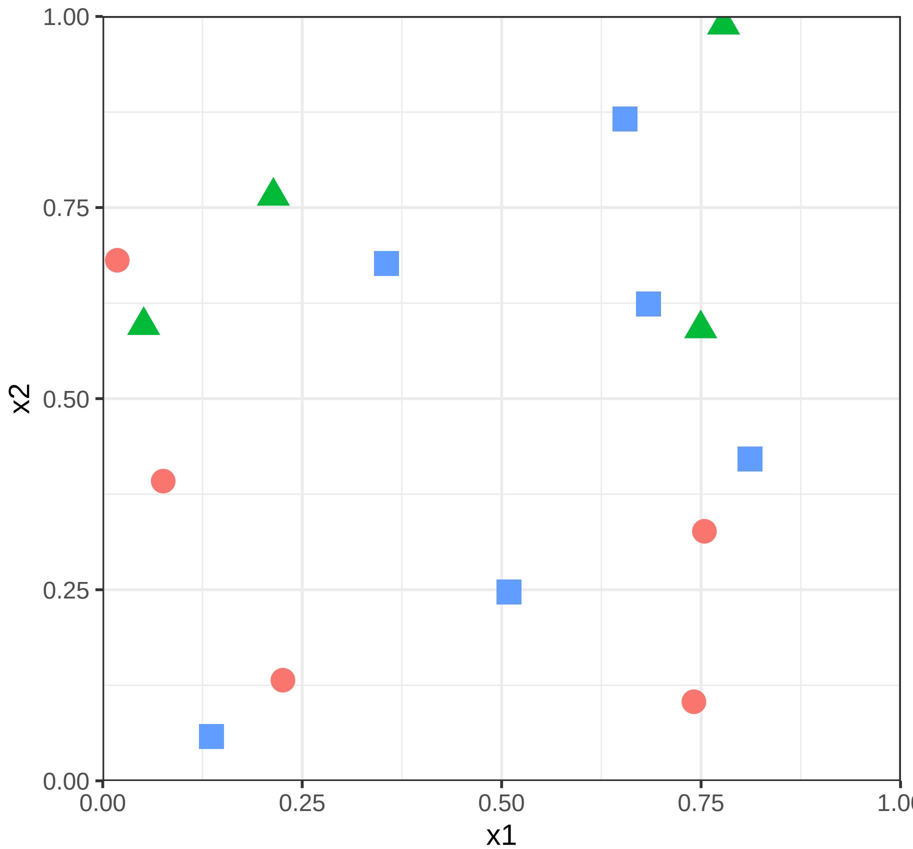
Lab 7: When a guest arrives they will count how many sides it has on

In class, we estimated by eye the first split in a classification tree for the following shapely data set. Now let's check to see if our graphical intuition agrees with that of the full classification tree algorithm.



1. Growing the full classification tree

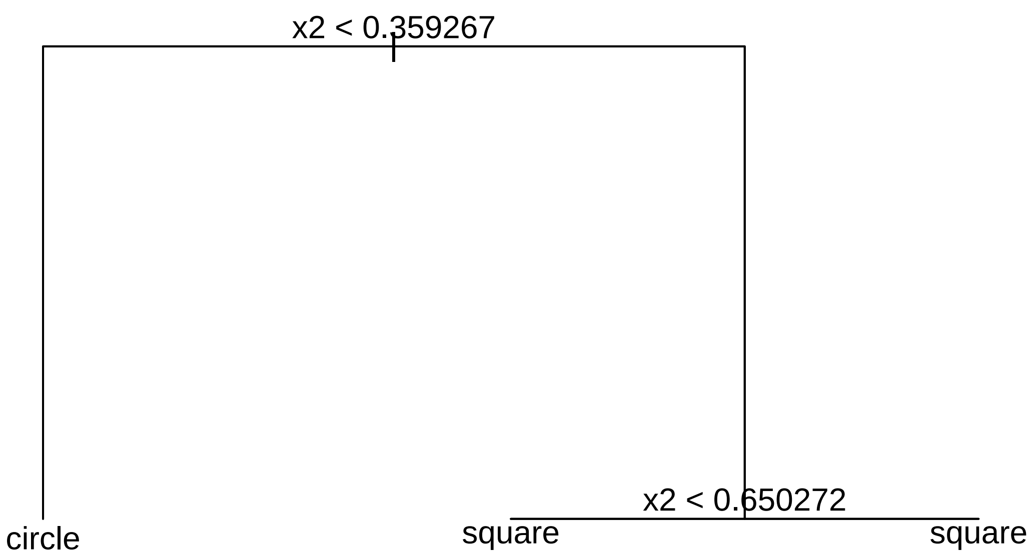
Use the `tree` package in R to fit a full unpruned tree to this data set, making splits based on the *Gini index*. You can find the code to do this in the slides from week 8 or in the lab at the end of Chapter 8 in the book. Please plot the resulting tree.

```
## -- Attaching packages --------------------------------------------- tidyverse 1.2.1 --
```

```
## v tibble  2.1.1     v purrr   0.3.2
## v tidyr   1.0.0     v dplyr   0.8.3
## v readr   1.3.1     v stringr 1.4.0
## v tibble  2.1.1     v forcats 0.4.0
```

```
## -- Conflicts -------------------------------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
```

```
## x dplyr::lag()    masks stats::lag()

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:dplyr':
##
##     combine

## The following object is masked from 'package:ggplot2':
##
##     margin
```



a. The two most common splits that we saw in class were a horizontal split around $X_2 \approx 0.50$ and a vertical split around $X_1 \approx 0.30$. Was either of these the first split decided upon by your classification tree?

No, the first split is x2 $<$ 0.359267

b. What is the benefit of the second split in the tree?

There is no benefit, if x2 is larger than or less than 0.650272 it will classified as a square.

c. Which class would this model predict for the new observation with $X_1 = 0.21, X_2 = 0.56$?

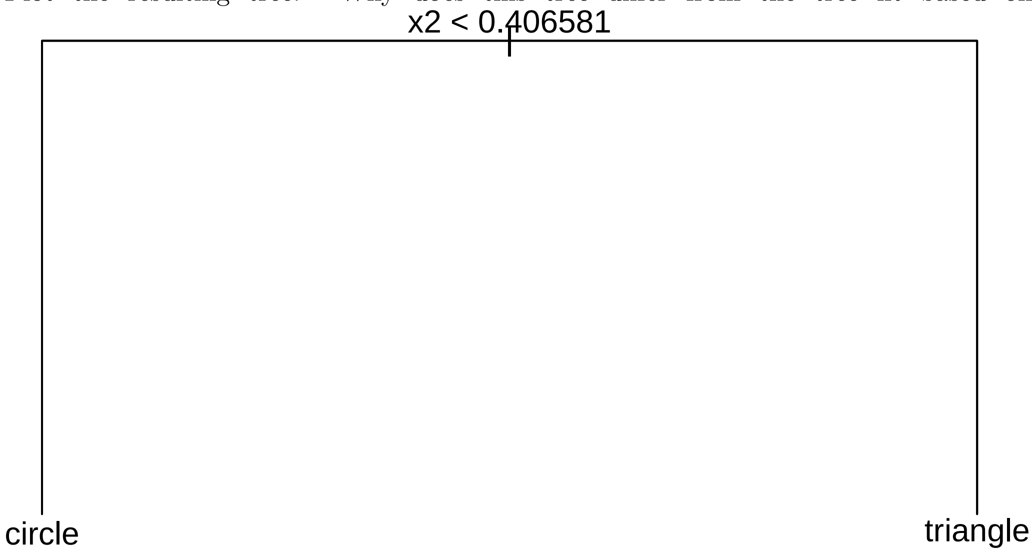
Square

2. An alternate metric

Now refit the tree based on the *deviance* as the splitting criterion (you set this as an argument to the `tree()` function). The deviance is defined for the classification setting as:

$$-2 \sum_m \sum_k n_{mk} \log \hat{p}_{mk}$$

Plot the resulting tree. Why does this tree differ from the tree fit based on the Gini Index?



Deviance is not scaled to account for the size, the number of obversations, or to account for their magnitude. It only fouses on the x2 variable while the Gini Index focuses only on the x1 variable.

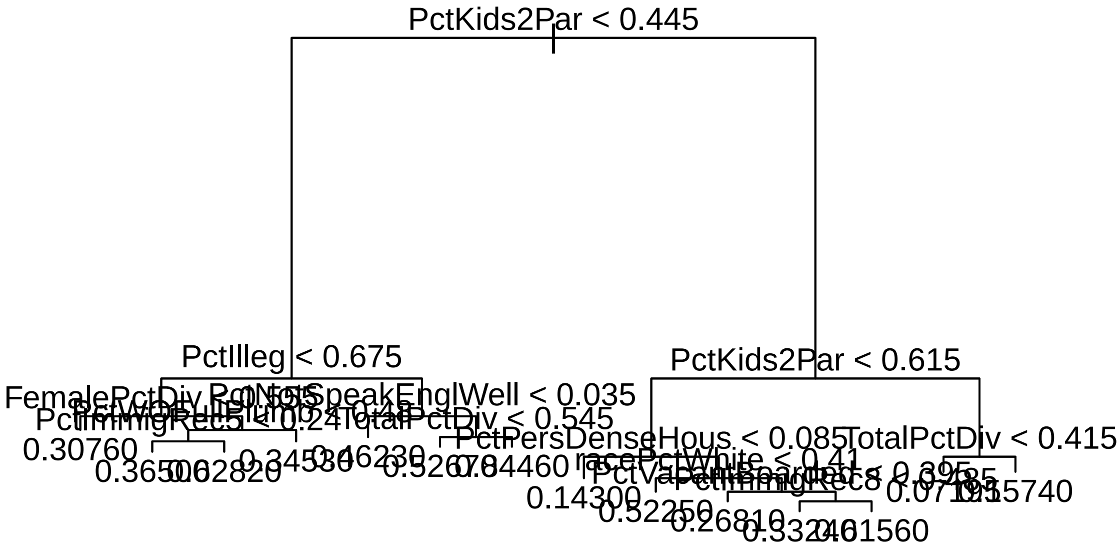
Crime and Communities, revisited

In Lab 3, you fit a regression model to a training data set that predicted the crime rate in a community as a function of properties of that community.

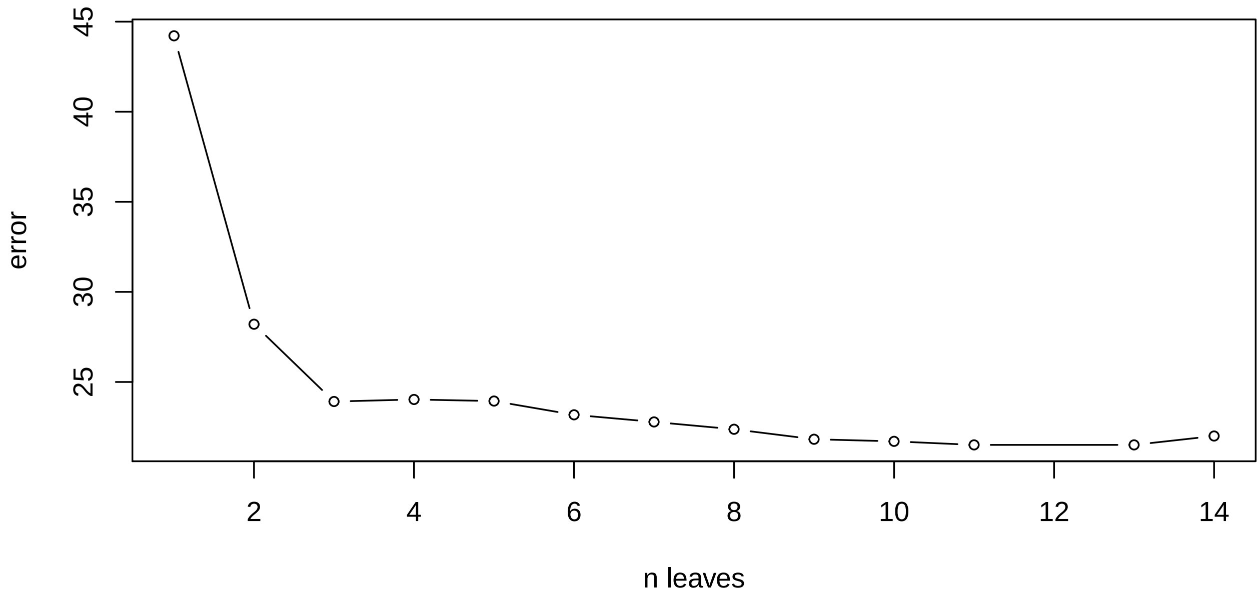
3. Growing a pruned regression tree

Fit a regression tree to the *training* data using the default splitting criteria (here, the deviance is essentially the RSS). Next, perform cost-complexity pruning and generate a plot showing the relationship between tree size and deviance to demonstrate the size of the best tree. Finally, construct the tree diagram for this best tree.

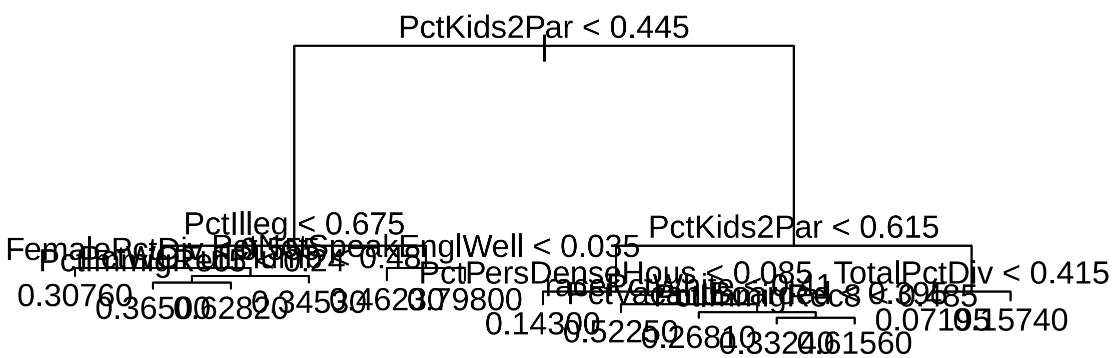
```
d <- read.csv("http://andrewpbray.github.io/data/crime-train.csv")
d[d=="?"]<-NA
d[d==""]<-NA

newd <- d %>%
  select(-c(state, county, community, communityname, population, LemasSwornFT, LemasSwFTPerPop,
            LemasSwFTFieldOps, LemasSwFTFieldPerPop, LemasTotalReq, LemasTotReqPerPop,
            PolicReqPerOffic, PolicPerPop, RacialMatchCommPol, PctPolicWhite, PctPolicBlack,
            PctPolicHisp, PctPolicAsian, PctPolicMinor, OfficAssgnDrugUnits, NumKindsDrugsSeiz,
            PolicAveOTWorked, PolicCars, PolicOperBudg, LemasPctPolicOnPatr, LemasGangUnitDeploy,
            PolicBudgPerPop)) %>%
  drop_na()
```



```
## $size
##  [1] 14 13 11 10  9  8  7  6  5  4  3  2  1
##
## $dev
##  [1] 22.00180 21.50829 21.50829 21.70486 21.82146 22.37553 22.78308
##  [8] 23.17809 23.94086 24.02890 23.91528 28.20549 44.21623
##
## $k
##  [1]       -Inf  0.5176420  0.5222261  0.5544045  0.6118008  0.7251080
##  [7]  0.7326129  0.8050502  1.1126087  1.1522867  2.0273988  4.1941945
## [13] 18.2672161
##
## $method
## [1] "deviance"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```




```
## [1] 13
```



4. Comparing predictive performance

Use this tree to compute the MSE for the *test* data set. How does it compare to the test MSE for your regression model? You can load the test data with the following code:

```
## [1] 0.01609171
```

```
##            2            7           10           12           13
## 0.5077756362 0.1615570852 0.1795327069 0.1596473765 0.1855321942
##           14           15           16           17           18
## 0.0977707260 0.0274269259 0.6140393420 0.0887156717 0.2413011778
##           24           25           26           27           28
## 0.2756914781 0.1804850461 0.0587666895 0.3333177318 0.0282717789
##           29           30           32           33           34
## 0.2387053299 0.6108551879 0.1228782809 0.1732975482 0.0367282902
##           36           38           39           40           41
## 0.1366395822 0.2705810767 0.1341163549 0.1084365643 0.1750330502
##           42           44           45           46           48
## 0.1121042630 0.0358421543 0.0025507056 0.0172657330 0.4786145554
##           50           51           52           53           54
## 0.4772403125 0.0866558071 0.2297997380 0.1293838005 0.1845492107
##           55           57           58           62           63
```

```
##  0.1201799772  0.1701217761  0.1941118604  0.0354456884  0.2298283019
##            65            74            76            77            78
##  0.2359131286  0.3739280393  0.2079520839  0.6050382894  0.6588015862
##            80            82            84            85            86
##  0.0173888880  0.1989682632  0.3999387859  0.3116705919  0.4604082926
##            88            96            98            99           102
##  0.2454571595  0.3280903009  0.0882523091  0.2871232473  0.1008405751
##           104           107           108           110           111
##  0.7883636290  0.0697171706  0.2699255819  0.6317559347  0.1483289933
##           113           114           115           117           119
##  0.4137805724  0.0590393069  0.1761895470  0.0676602559  0.2809039335
##           120           122           125           129           131
##  0.1165236106  0.1016847347  0.4346332175  0.1788772121  0.3858764794
##           134           135           136           137           138
##  0.2266523536  0.0515514972  0.3759736220  0.0350911988  0.0706445894
##           139           140           142           143           144
##  0.1778835901  0.1893636372  0.5833829436  0.3030262854  0.3348421305
##           145           146           147           148           151
##  0.1187322442  0.3314756132  0.0347915805  0.7145265131  0.2898927846
##           153           155           156           158           159
##  0.1392460686  0.2047890307  0.0221484432  0.1026534363  0.3833652775
##           160           161           166           167           168
##  0.4228242947  0.5125871128  0.2817345047  0.1977135319  0.3567303739
##           173           175           176           178           179
##  0.2525485033  0.5590789590  0.2769064896  0.1657031220  0.4410951978
##           183           184           185           187           188
##  0.6616139693  0.0863568822  0.3519159474  0.1827499380  0.5090545946
##           192           193           197           198           199
##  0.3043893724  0.0418686424  0.0940767200  0.8537705412  0.1169869732
##           200           203           204           207           209
##  0.2261499647  0.3952746913  0.1531411634  0.1501552669  0.0794143074
##           210           211           212           215           216
##  0.2934230463  0.0146080187  0.0998042833  0.4223046739  0.1123911624
##           218           219           221           223           226
##  0.1546821006  0.5103777857  0.2021832378  0.3137027622  0.0699634806
##           228           230           232           233           235
##  0.5005454685  0.1747033050  0.3244759105  0.0351467636  0.3987260308
##           237           240           242           245           249
##  0.3356899336  0.5145231290  0.2507363356  0.4123748156  0.0683939795
##           251           253           255           256           258
##  0.0320896335  0.3533366796  0.0841325798  0.0802185711  0.2432351136
##           259           260           267           268           269
##  0.3295373405  0.4518422148  0.6445251770  0.4377300674  0.3630301729
##           270           271           275           277           283
##  0.1369534824  0.0675904092 -0.0016216385 -0.0057819572  0.1941089104
##           289           290           292           293           295
##  0.2947598259  0.1375527189  0.3932831104  0.1487082273  0.7135705304
##           297           299           302           303           305
##  0.2300032021  0.0348321699  0.0966525621  0.3883321164  0.2277029274
##           306           308           310           314           315
##  0.3375973859  0.2904237374  0.2126027661  0.1308564541  0.1538522229
##           316           326           331           334           342
##  0.3761786492  0.4393671588  0.1514371752  0.0443249729  0.2270181752
##           343           344           346           347           348
```

```
##  0.0261863003  0.1451487082  0.3330961661  0.1550230017 -0.0399039770
##           350           352           355           358           364
##  0.1281424816  0.2630505973  0.1991447265  0.1739539126  0.0771793664
##           365           366           370           371           373
##  0.2633502156  0.6601660601  0.2269775859  0.3699763912  0.0930937365
##           376           377           378           379           380
##  0.0664309624  0.2811194231  0.1544380471  0.4465118108  0.2143487305
##           382           383           386           387           390
##  0.2700194796  0.5254216888  0.4775662381  0.7367720199  0.0398913434
##           392           393           394           395           396
##  0.1032955187 -0.0057000850  0.2290923218  0.0937748452  0.2009988705
##           398           399           404           405           408
##  0.1451636836 -0.0329350947  0.6933216349  0.2688593393  0.6840998862
##           413           418           419           424           426
##  0.0989301728  0.0600080084  0.3247365025  0.1996749859  0.2476785120
##           431           434           437           439           440
##  0.1559647024  0.3581916955  0.1048094550  0.0684368253  0.1606559739
##           441           444           445           448           449
##  0.1284443563  0.0392102347  0.0427960611  0.3264291586  0.2573080585
##           451           454           455           460           465
##  0.1590601654  0.1509062224  0.2546390123  0.1543824823  0.1085860267
##           468           469           470           471           473
##  0.0289408622  0.6337346207 -0.0545514142  0.4005209666  0.2501754319
##           474           475           476           477           480
##  0.2887573887  0.5143616411  0.3299743957  0.1431863846  0.1440319312
##           481           482           483           489           490
##  0.0650664885  0.0911833342  0.1084095635  0.0114150147  0.3107318412
##           491           492           493           494           497
##  0.2093308398  0.0279578787  0.1699017735  0.3495308505  0.1222917632
##           498           502           503           504           505
##  0.0995053585  0.1491452825  0.0890978556  0.3699051576  0.3510597623
##           507           509           515           516           517
##  0.4074245152  0.0782149647  0.5749940226  0.2120981206  0.3081260482
##           519           523           525           527           529
##  0.4002970950  0.2128640515  0.4125948182  0.3511116837  0.2373971141
##           530           533           534           535           536
##  0.0951551642 -0.0006003222  0.1769817853  0.7838773847  0.0708652854
##           537           545           547           548           549
##  0.4942833089  0.1468270824  0.2497134562  0.5597893251  0.3705157261
##           550           554           555           557           558
##  0.7376581558  0.1049446355  0.2311912128  0.8623495139  0.1198504081
##           561           562           563           564           565
##  0.0436821970  0.0663078074  0.4259986799  0.1699573382  0.2948011087
##           566           567           568           570           571
##  0.4190567985  0.1771169657  0.2368008276  0.0705506917  0.0816093525
##           572           573           575           576           577
##  0.0935307917  0.4498821477  0.4016157731  0.1294799547 -0.0144968039
##           578           581           582           587           589
##  0.4480790555  0.2768254870 -0.0041185584  0.1959367470  0.3175625930
##           590           591           593           595           597
##  0.2783784497  0.3484426374  0.3223064793  0.1704882911  0.0523324035
##           599           602           605           606           611
##  0.1915593758  0.2549778330  0.3382095175  0.1439223647  0.4340031605
##           612           613           615           616           622
```

```
##  0.2191908514  0.2304831032  0.5083578170  0.0892060352  0.4008244044
##           623           627           631           632           633
##  0.2400591653  0.5109402525  0.3452346580  0.3062306214  0.0629540090
##           635           637           638           639           640
##  0.2625715658  0.3330172439  0.3152713938  0.1961567497  0.2271427171
##           642           643           650           651           653
##  0.1566067848  0.2811194231  0.1127876282  0.3022739430  0.0990832787
##           655           657           658           661           662
##  0.2443133816  0.0868472457  0.1212824723  0.3675313927  0.1546430743
##           663           664           667           668           671
##  0.0146479146  0.1834723295  0.3249685305  0.2133416961  0.1702862139
##           674           675           676           677           678
##  0.0602806258  0.2746318289  0.2095778433  0.3996241922  0.4708157954
##           679           681           686           687           688
##  0.4173942693  0.2380918114  0.3012773710  0.1699573382  0.1489275364
##           691           695           699           700           701
##  0.0984135019  0.1617065476  0.1658931737  0.0566249526  0.3474972933
##           702           703           705           710           714
##  0.1418482181  0.0399874975  0.3804507909 -0.0228970569  0.4338679801
##           715           717           718           719           720
##  0.1238619579  0.0309451621  0.0541835975  0.1573847411  0.4576117544
##           721           725           727           728           730
##  0.2586169677  0.0970347460  0.7132738621  0.3131582208  0.0665804248
##           731           733           736           739           740
##  0.1719759201  0.2394547223  0.2315613713  0.7662426641  0.3131845283
##           741           744           745           746           747
##  0.1640930314  0.2039149202  0.2340839051  0.1305425538  0.1272706276
##           749           753           756           757           759
##  0.4715810328  0.2654363876  0.0219982874  0.2570916994  0.2326225835
##           760           761           763           765           767
##  0.2895382950  0.3622529101  0.8151203007  0.2228871139  0.0006139959
##           775           778           783           784           785
##  0.2481711320  0.4137655970  0.2314082654  0.3191057868  0.1985987982
##           786           788           791           792           794
##  0.0535024888  0.0644672519  0.1976443786  0.3533772690  0.0519885524
##           797           798           800
##  0.4366389043  0.4633542931  0.2264466330
```

```
## [1] 0.02320641
```

The MSE for my tree model is 0.01609171 and the MSE for my linear regression model is 0.02320641. The predictive performance of the tree model is better than the regression model since the mean squared error is smaller.

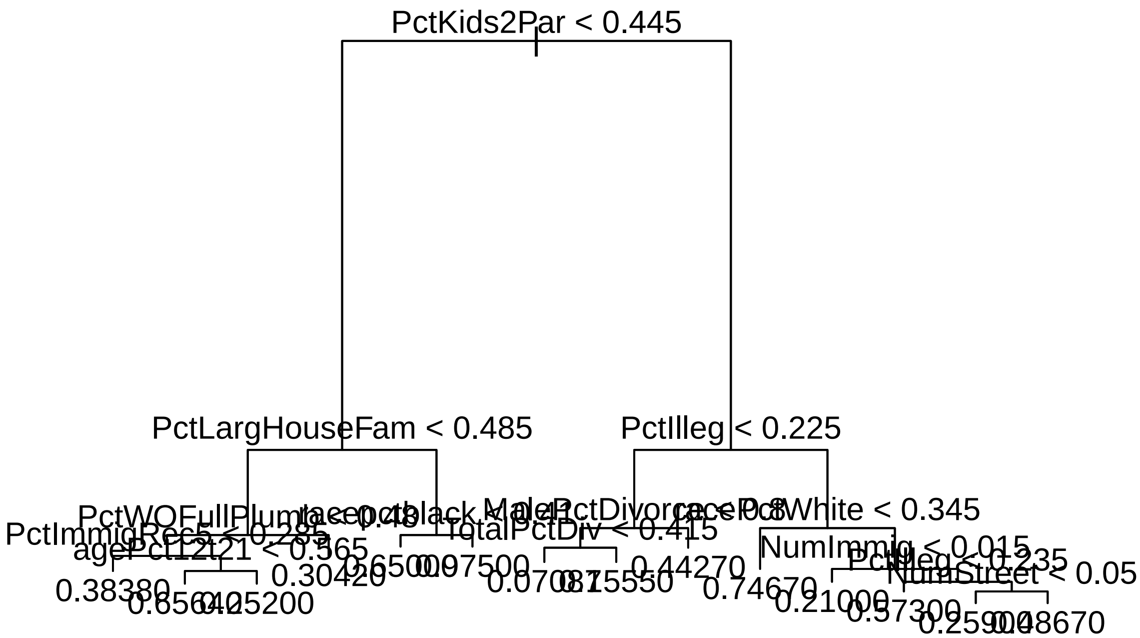
5. Growing a random forest

We now apply methods to decrease the variance of our estimates. Fit a `randomForest()` model that performs only bagging and no actual random forests (recall that bagging is the special case of random forests with $m = p$). Next, fit a second random forest model that uses $m = p/3$. Compute their test MSEs. Is this an improvement over the vanilla pruned regression tree? Does it beat your regression model?

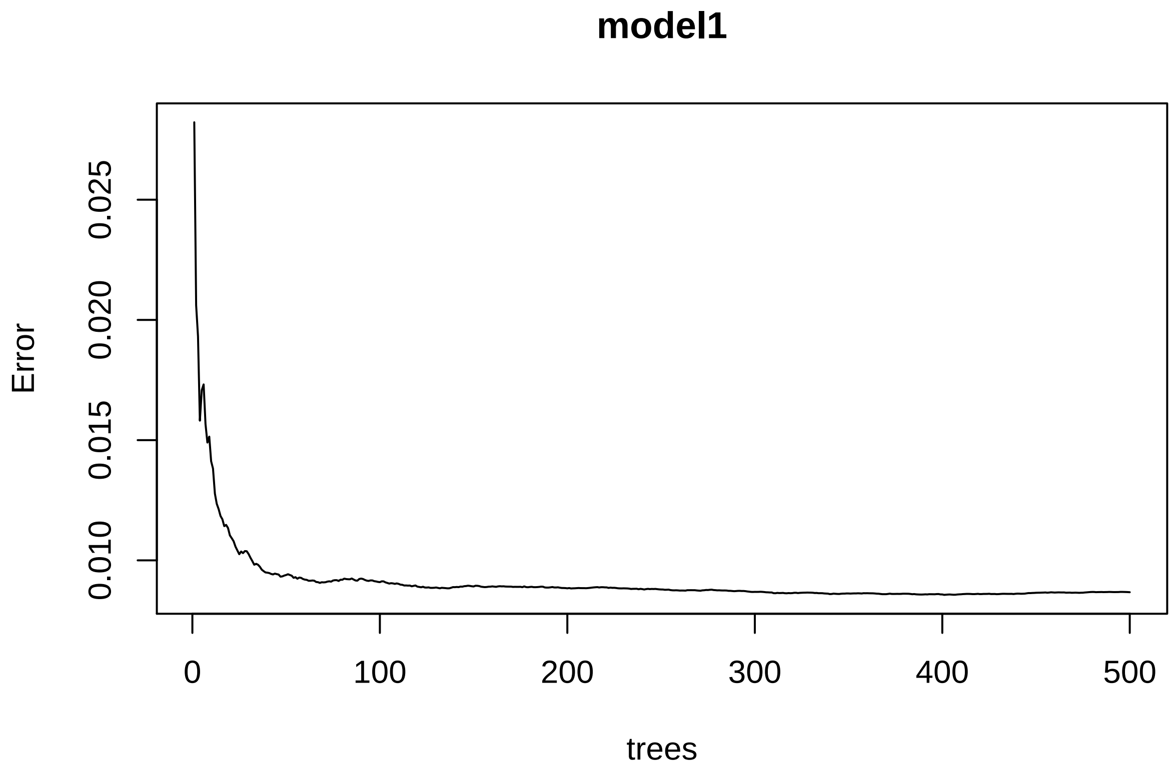
```
##  [1] 12 26  9 47 16 41 96 81 43 79 29 65 13 36 38 54 73
## [18] 18  3 24 63 92 25 27 15 80 21 83 76 40 97 62 32 35
## [35] 94 14 61 85 48 49 78 88 60 31 50 28 52 34 53 37 74
## [52] 82 98 91  6 39 56  7 57 33 19 87 64 30 66 59  1 46
```

```
## [69]  42  71  69  86  75  93  58 100  90  77  20  10  84  55  17  99  11
## [86]  45   4  44  23  67  70  22  95   2  72   5   8  51  89  68
```

```r
#First Random Split
library(tree)
rftree <- tree(ViolentCrimesPerPop ~ .-ViolentCrimesPerPop,
               data = crim_rforest)
plot(rftree)
text(rftree, pretty = 0)
```



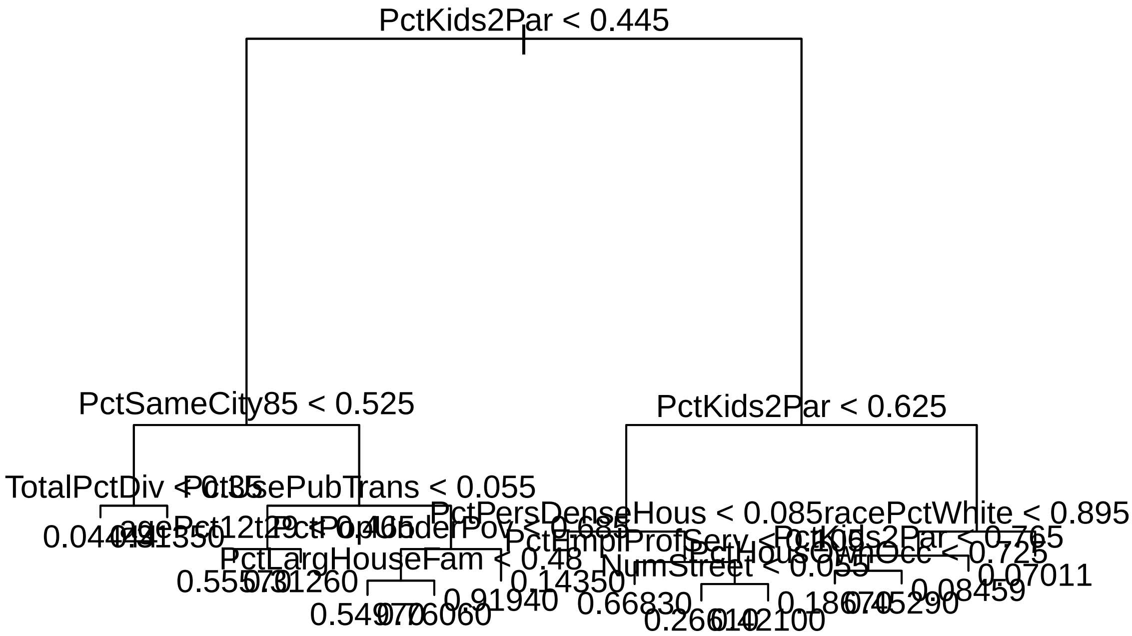

```
##
## Call:
##  randomForest(formula = ViolentCrimesPerPop ~ . - ViolentCrimesPerPop,      data = crim_rforest, imp
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 33
##
##           Mean of squared residuals: 0.008674571
##                     % Var explained: 86.98
```



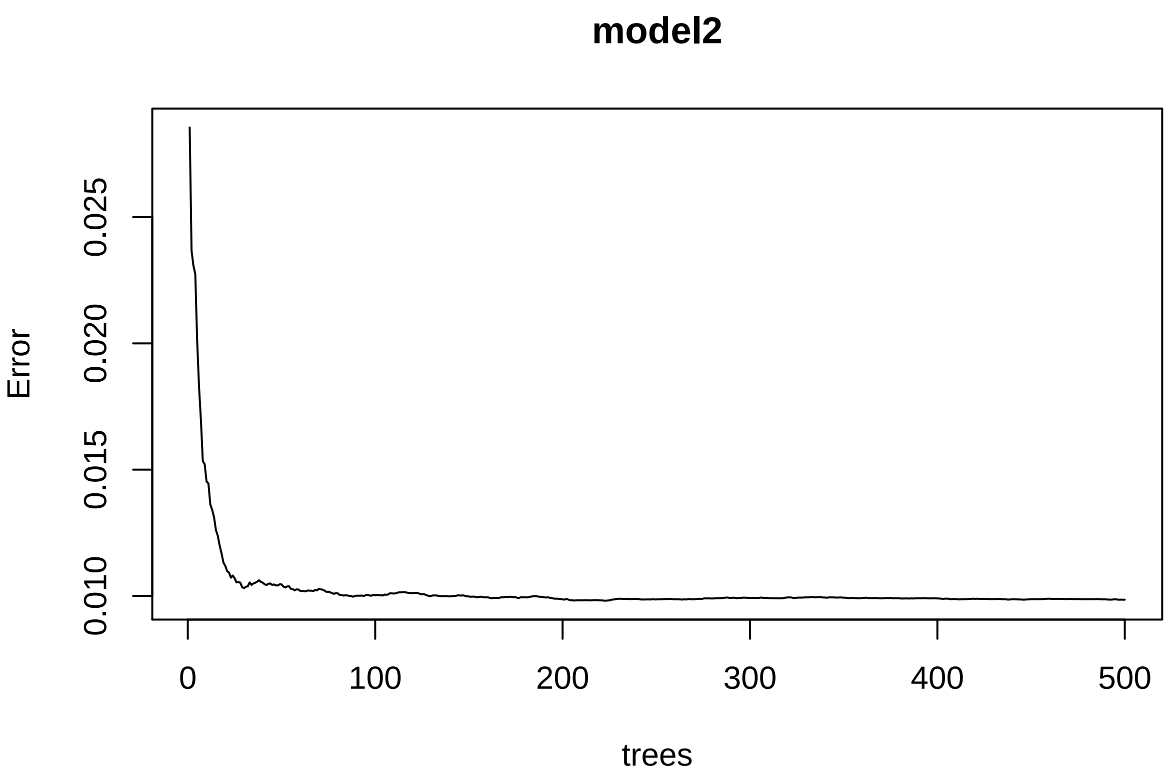

```
## [1] 0.001341236
```

```
##   [1]  87  42  82  53  31  40   5  45  97  37  77   6  62  69  21  30  65
##  [18]  90  55  20  86  32  14  11  26  34  50  72  60  49  36  70  47  19
##  [35]  17  66  98  85  73  80  41  16  27  43 100  29  81   2  88  74  22
##  [52]  23  38  18  59  12  54  25  52  99  39  71   4  68  57  92   9  89
##  [69]  67  96  56  44  28  75  10   3  64  35  63  24  51  48  33  79  58
##  [86]   7  83  46  13  84   8  15  93   1  76  78  91  61  94  95
```

```r
#First Random Split
rftree2 <- tree(ViolentCrimesPerPop ~ .-ViolentCrimesPerPop,
                data = crim_rforest2)
plot(rftree2)
text(rftree2, pretty = 0)
```




```
##
## Call:
##  randomForest(formula = ViolentCrimesPerPop ~ . - ViolentCrimesPerPop,      data = crim_rforest2, imp
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 33
##
##           Mean of squared residuals: 0.009848266
##                     % Var explained: 80.07
```



```
## [1] 0.1073736
```

The test MSE for the random forest with $m = p$ is 0.001511666. The test MSE for the random forest with $m = p/3$ is 0.001485386. Yes, the test MSE's from these random forests are much smaller than the singular pruned regression tree and my regression model, thus the predictive performance of the random forests is higher than all other methods.

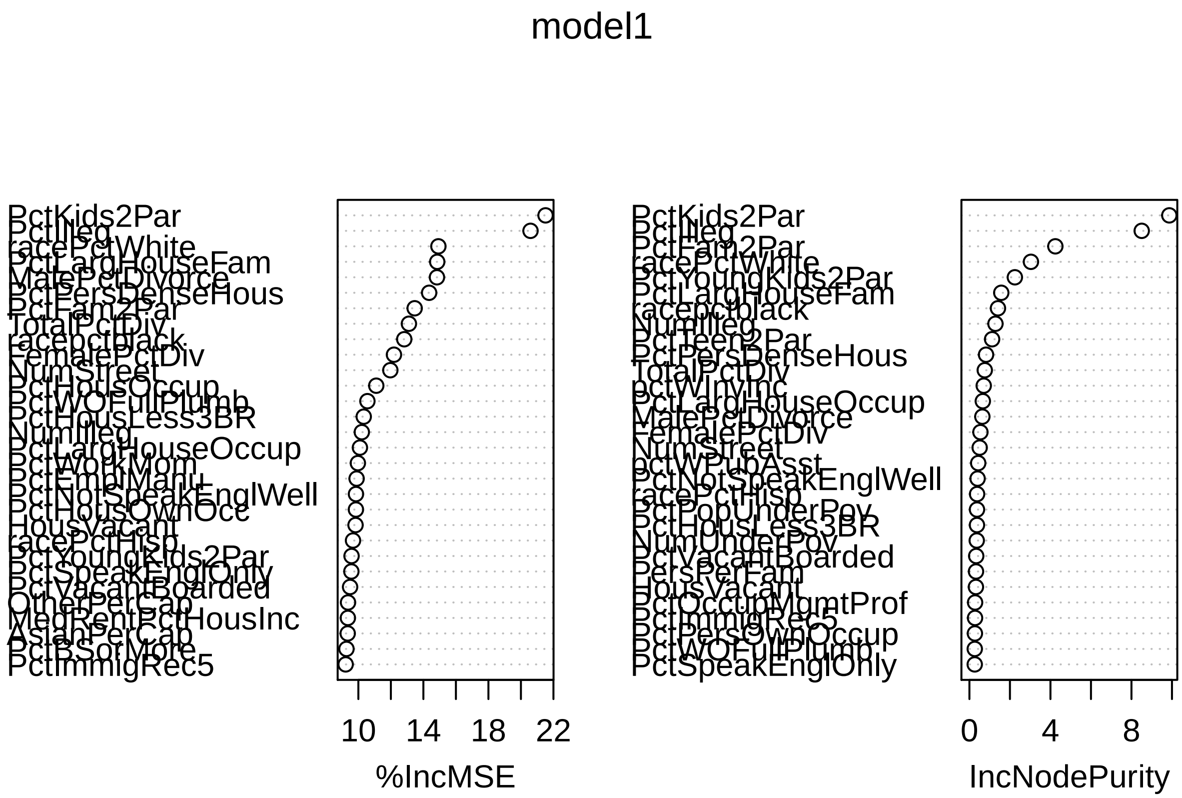
6. Variance importance

One thing we lose by using these computational techniques to limit the variance is the clearly interpretable tree diagram. We can still salvage some interpretability by considering `importance()`. Please construct a Variable Importance Plot (`varImpPlot()`). Are these restults similar/different from your interpretation of your regression coefficients in Lab 3?

```
##                       %IncMSE IncNodePurity
## medIncome            6.858889    0.09081510
## HispPerCap           7.986216    0.21745097
## agePct65up           6.408117    0.10351589
## PctWorkMomYoungKids  8.610607    0.22077344
## pctWSocSec           6.969395    0.08977911
## TotalPctDiv         13.109434    0.75754594
## LandArea             6.929442    0.14807714
## OwnOccHiQuart        5.321689    0.06389573
## PctFam2Par          13.464068    4.24204188
## OwnOccLowQuart       4.671621    0.05975020
## PctLess9thGrade      6.896907    0.15924047
## PersPerOwnOccHous    6.576430    0.13575957
## pctWWage             5.422339    0.08757720
## PctOccupManu         7.507206    0.17830847
## MalePctDivorce      14.834560    0.63753429
## PctImmigRec8         8.333166    0.25111644
## PctHousOwnOcc        9.849114    0.16562367
## pctWRetire           7.396598    0.14504682
## racePctWhite        14.923650    3.03763705
## AsianPerCap          9.344940    0.24754819
## PctLargHouseOccup   10.094698    0.66123513
## PctBornSameState     7.244834    0.13321280
## OtherPerCap          9.364202    0.21137791
## NumUnderPov          9.137963    0.36128725
## pctWInvInc           7.531950    0.70621797
## OwnOccMedVal         5.001567    0.06818987
## whitePerCap          5.220883    0.10001072
## RentMedian           3.912584    0.07589785
## MedYrHousBuilt       8.555089    0.11296170
## FemalePctDiv        12.188727    0.54393630
## PopDens              6.440771    0.12792815
## PctLargHouseFam     14.851255    1.57273738
## PctUnemployed        8.273687    0.14961831
## PctEmplProfServ      7.665463    0.12880425
## PctSameCity85        7.329234    0.13930508
## pctWFarmSelf         8.872675    0.20577278
## PctNotSpeakEnglWell  9.853215    0.40340010
## MedRent              5.300422    0.08243621
## PctWorkMom           9.969609    0.18672818
## NumIlleg            10.212157    1.28483882
```

```
## PctWOFullPlumb        10.556328    0.26383559
## MedOwnCostPctIncNoMtg  8.754623    0.22777281
## PctSpeakEnglOnly       9.568818    0.26276351
## PctBSorMore            9.269272    0.20625479
## PctIlleg              20.589666    8.50646416
## PctPopUnderPov         5.118246    0.37358288
## PctImmigRecent         8.120799    0.19538349
## PctEmplManu            9.892605    0.25186262
## PctImmigRec5           9.218459    0.27734310
## PctOccupMgmtProf       8.460065    0.27997620
## PctVacantBoarded       9.490273    0.33495296
## RentLowQ               5.885813    0.08694492
## PctUsePubTrans         9.104368    0.21435058
## PctForeignBorn         8.339506    0.25043842
## agePct12t21            6.097533    0.11164408
## MalePctNevMarr         6.263827    0.24675743
## PctRecentImmig         7.477419    0.24248424
## agePct12t29            8.457887    0.15558959
## PctRecImmig5           6.188038    0.14169678
## PctEmploy              6.274396    0.08298581
## medFamInc              6.043858    0.10817869
## MedOwnCostPctInc       8.300451    0.18832516
## PersPerOccupHous       6.350249    0.10480105
## PctNotHSGrad           5.393053    0.24996089
## PersPerRentOccHous     6.867739    0.15012659
## PctRecImmig10          6.914944    0.13206538
## householdsize          8.077629    0.12472826
## PctTeen2Par            8.658936    1.11988995
## PersPerFam             7.698397    0.32424964
## HousVacant             9.827179    0.32051894
## PctHousLess3BR        10.330663    0.37166656
## MedRentPctHousInc      9.354407    0.24480423
## PctVacMore6Mos         7.387387    0.09898758
## PctSameHouse85         8.410314    0.12990667
## PctRecImmig8           6.080823    0.13963158
## NumStreet             11.966957    0.50637704
## PctHousNoPhone         7.563916    0.15654896
## perCapInc              5.915022    0.07061432
## numbUrban              8.269738    0.19298424
## RentHighQ              4.875286    0.08348235
## PctImmigRec10          7.618937    0.19507328
## pctWPubAsst            5.782141    0.43448420
## LemasPctOfficDrugUn    6.273897    0.07518718
## pctUrban               4.137235    0.05045731
## PctYoungKids2Par       9.581060    2.24365851
## racePctAsian           8.267959    0.12767041
## PctKids2Par           21.514627    9.86820639
## indianPerCap           8.641653    0.19043901
## PctPersOwnOccup        8.552604    0.27069970
## MedNumBR               2.669066    0.02687316
## blackPerCap            7.899180    0.15597152
## PctSameState85         8.928798    0.15774152
## racepctblack          12.821883    1.40950633
## PctHousOccup          11.100250    0.26006245
```

```
## racePctHisp            9.669970    0.37825787
## agePct16t24            7.034795    0.14538911
## NumImmig               6.534182    0.10098512
## NumInShelters          5.490711    0.10063479
## PctPersDenseHous      14.353333    0.82155830
## pctWWage.1             7.107540    0.07943939
```



The variable importance plots show very similar results to what I interpreted were the more important variables. For my regression model, I chose the variables PctFam2Par, racePctWhite, and PctPersOwnOccup. PctPersOwnOccup was less important according to the random forests, which is where my interpretation of the most impactful predictors varied slightly.