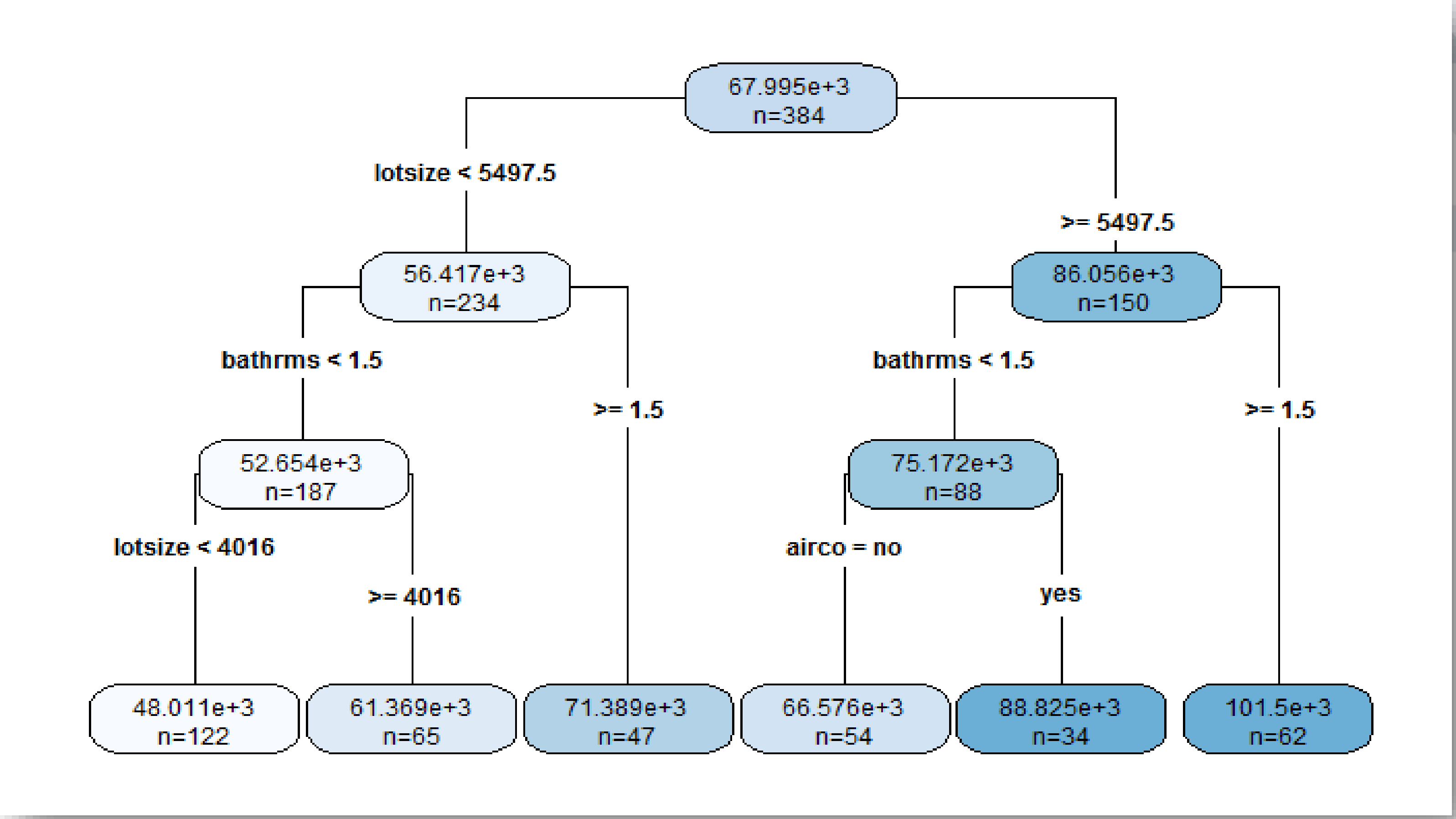
Regression Tree

Typical Regression Tree Output

- In case of regression trees, the difference is that on the leaf nodes we have the means of the response variable values.



Regression Tree

- The data gets divided into two parts in the interest of decreasing the variation of response variable
- The child nodes have lesser variation than their respective parent nodes for response variable

Regression Tree in R

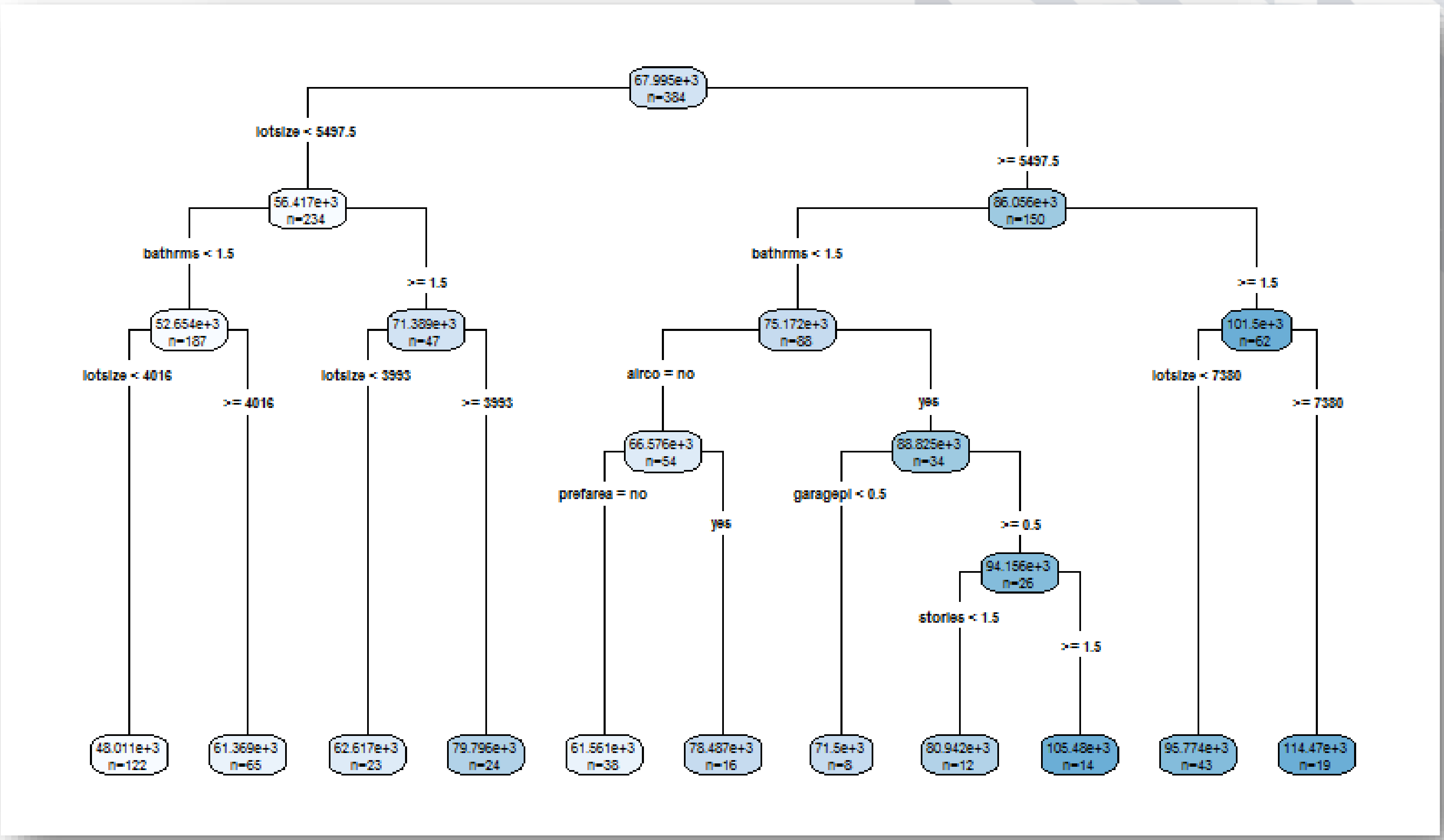
- For implementing Regression Tree in rpart( ), option method should be specified with "anova".
- For implementing Regression Tree in ctree( ), there is no option to be specified differently. It identifies the response variable type and executes accordingly

Example : Sales Prices of Houses in the City of Windsor

- **Description**
  - a cross-section from 1987
  - *number of observations* : 546
  - *country* : Canada
- A dataframe containing :
  - **price :** sale price of a house
  - **lotsize :** the lot size of a property in square feet
  - **bedrooms :** number of bedrooms
  - **bathrms :** number of full bathrooms
  - **stories :** number of stories excluding basement
  - **driveway :** does the house has a driveway ?
  - **recroom :** does the house has a recreational room ?
  - **fullbase :** does the house has a full finished basement ?
  - **gashw :** does the house uses gas for hot water heating ?
  - **airco :** does the house has central air conditioning ?
  - **garagepl :** number of garage places
  - **prefarea :** is the house located in the preferred neighbourhood of the city ?

Program and Output – Using rpart

```
rpart.plot(fitRT,type = 4,extra = 1, digits = 5)
```



Model Evaluation: RMSE

- RMSE : Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum (y_i - \widehat{y_i}\ )^2}{n}}$$

where

y_i = Observed Values
$\widehat{y_i}$ = Predicted Values
n = No. of observations

Model Evaluation: MAPE

- MAPE: Mean Absolute Percentage Error

$$\text{MAPE} = \frac{\sum\left|\frac{y_i - \widehat{y_i}}{y_i}\right|}{n}$$

- Where

y_i = Observed Values

$\widehat{y_i}$ = Predicted Values

n = No. of observations

Model Evaluation: RMSPE

- RMSPE: Root Mean Square Percentage Error
  - Often used at Kaggle competitions

$$\text{RMSPE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2}$$

- Where

y_i = Observed Values

$\hat{y}_i$ = Predicted Values

n = No. of observations

Model Evaluation in R

- About MAPE, RMSE and RMPSE, only one criterion holds: **Smaller** their value, **Better** is the model prediction
- RMSE is calculated as directly by function postResample( )
- For MAPE and RMSPE we can create a functions

```
MAPE <- function(y, yhat) {
  mean(abs((y - yhat)/y))
}
```

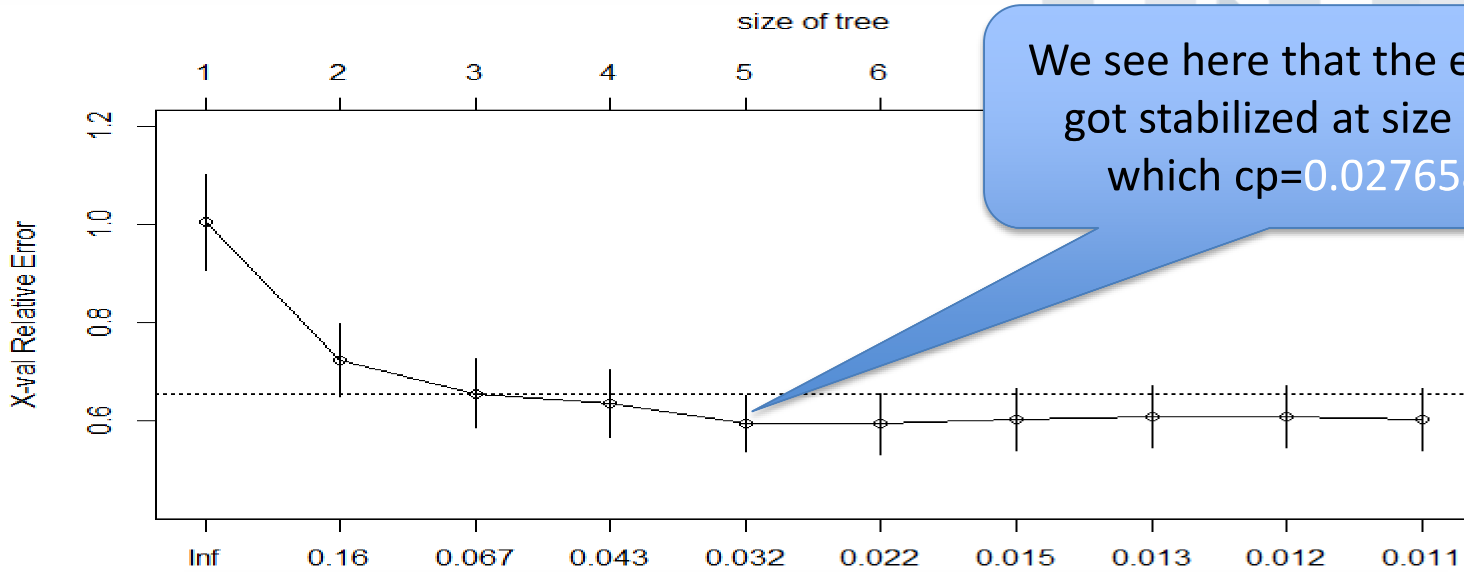
```
RMPSE<- function(y, yhat) {
  sqrt(mean((y-yhat)/y)^2)
}
```

Output

```
> pred.RT <- predict(fitRT,newdata = validation )
>
> postResample(pred.RT , validation$price)
        RMSE     Rsquared
1.809074e+04 5.414778e-01
>
> MAPE <- function(y, yhat) {
+   mean(abs((y - yhat)/y))
+ }
>
> MAPE(validation$price , pred.RT)
[1] 0.2036191
>
> RMSPE<- function(y, yhat) {
+   sqrt(mean((y-yhat)/y)^2)
+ }
>
> RMSPE(validation$price , pred.RT)
[1] 0.04037694
>
```

Pruning

- We take a look at plotcp( ) output

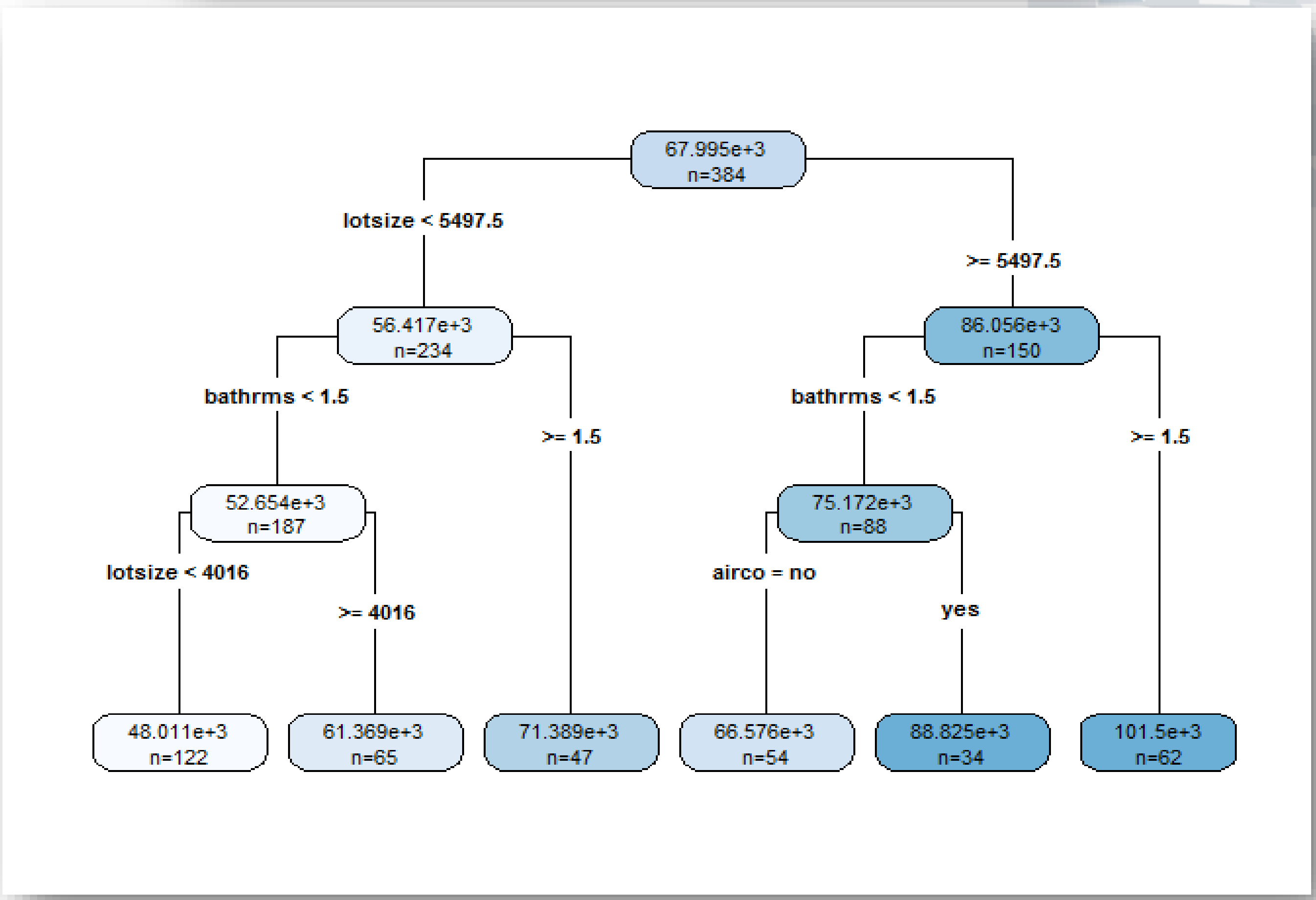


We see here that the error has got stabilized at size = 5 for which cp=0.02765860.

```
> fitRT$cptable
           CP nsplit rel error    xerror       xstd
1  0.29348617      0 1.0000000 1.0051535 0.09724243
2  0.09217662      1 0.7065138 0.7250328 0.07373928
3  0.04818811      2 0.6143372 0.6572006 0.06866341
4  0.03775017      3 0.5661491 0.6367268 0.06719953
5  0.02765860      4 0.5283989 0.5957366 0.05874151
6  0.01683250      5 0.5007403 0.5945977 0.06134276
7  0.01285050      6 0.4839078 0.6042144 0.06289123
8  0.01266817      8 0.4582068 0.6093850 0.06347051
9  0.01179162      9 0.4455387 0.6086444 0.06344482
10 0.01000000     10 0.4337470 0.6039693 0.06348830
```

Pruning

```
fitRT.pruned <- prune(fitRT , cp=0.02765860  )
```



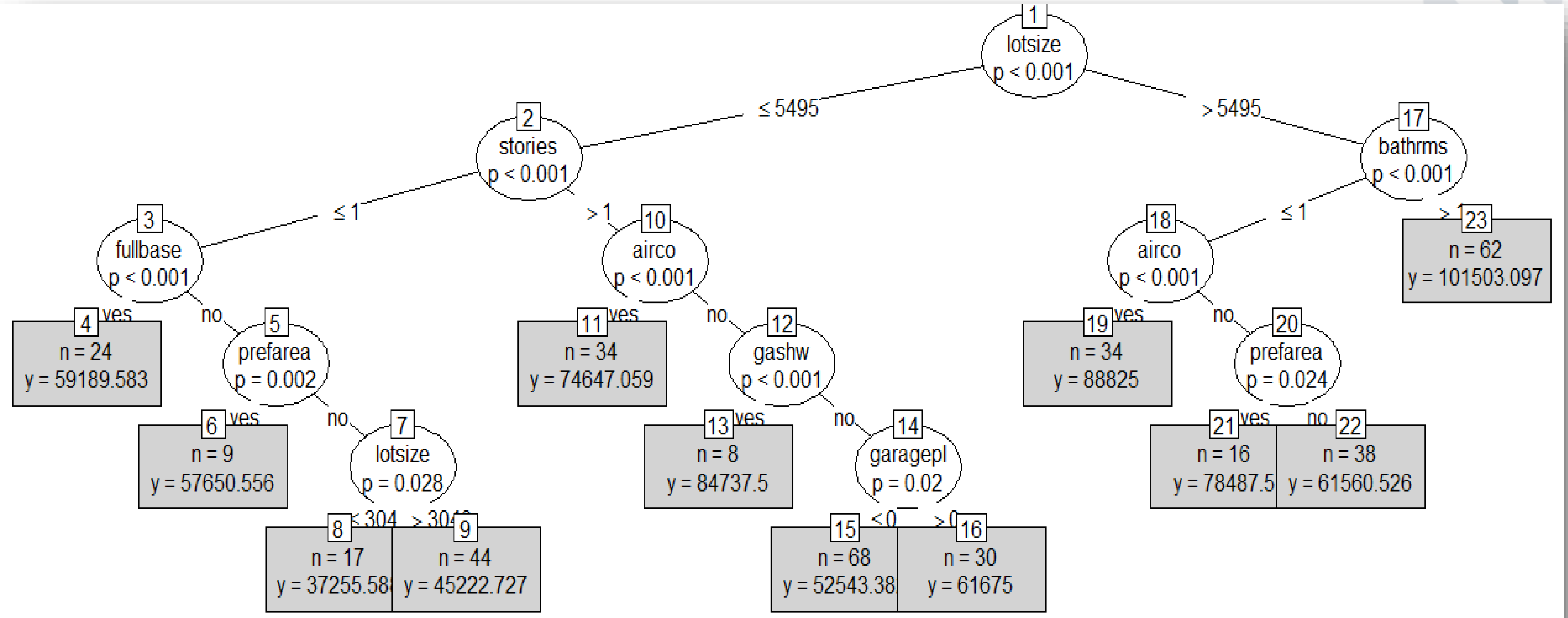
Output

```
> pred.RT.pruned <- predict(fitRT.pruned , newdata = validation)
> postResample(pred.RT.pruned , validation$price)
        RMSE     Rsquared
1.895032e+04 4.967799e-01
> MAPE(validation$price , pred.RT.pruned)
[1] 0.2180033
> RMSPE(validation$price , pred.RT.pruned)
[1] 0.04583555
```

Though we might observe that the accuracy has been affected negatively by pruning, still we have minimized the risk of overfitting of the model

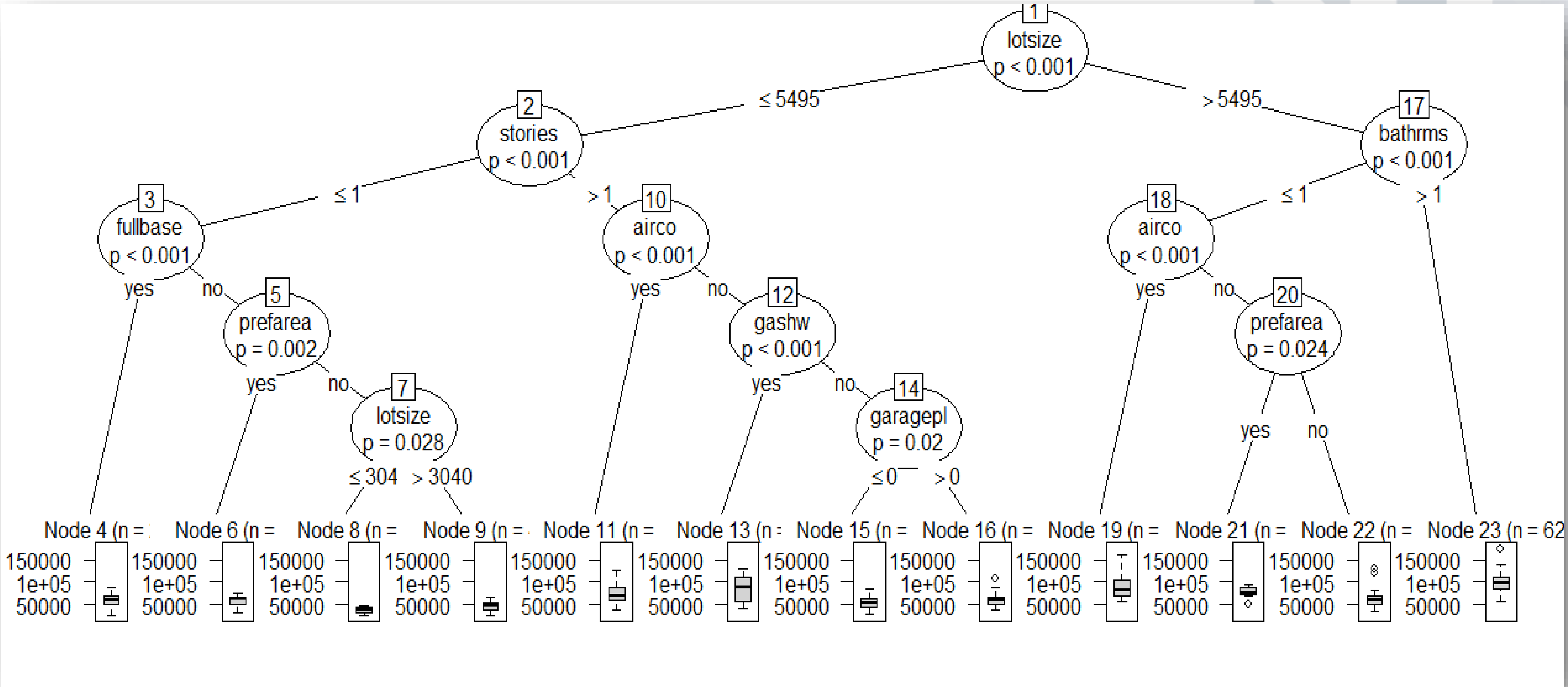
Program and Output – Using party

```
library(party)

fitCT <- ctree(price ~ . , data = training )

plot(fitCT , type="simple")
```



Program and Output – Using party

```
plot(fitCT , type="extended" )
```



Accuracy Measures : party

```
> pred.CT <- predict(fitCT , newdata=validation)
>
> postResample(pred.CT , validation$price)
        RMSE     Rsquared
1.831758e+04 5.279237e-01
> MAPE(validation$price , pred.CT)
[1] 0.2145092
> RMSPE(validation$price , pred.CT)
[1] 0.06729213
```