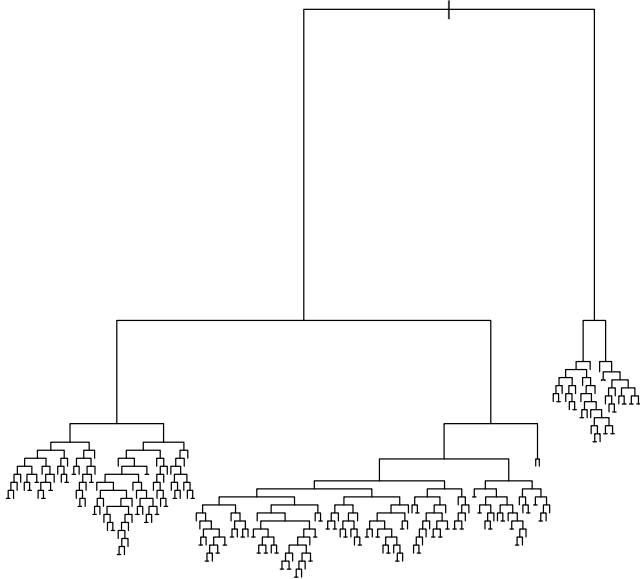


# STAT406- Methods of Statistical Learning Lecture 11

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# Overfitting...



# Boston Example

Not surprisingly, when we overfit...

```
> pr.to <- predict(bos.to,  
  newdata=dat.te,  
  type='vector')  
> with(dat.te, mean((medv - pr.to)^2))  
[1] 36.51097
```

# Pruning...

- Cost pruning

$$\min_{T \subset T_0} \sum_{m=1}^{|T|} \sum_{\mathbf{x}_i \in R_m} (y_i - \hat{\mu}_m)^2 + \alpha |T|$$

- We can compute the solution for all  $\alpha$
- Compare each subtree in this sequence using CV
- Pick the best subtree

# Pruning...

- More specifically:
- Let  $T_\ell \subset T_0$  be the solution to

$$\min_{T \subset T_0} \sum_{m=1}^{|T|} \sum_{\mathbf{x}_i \in R_m} (y_i - \hat{\mu}_m)^2 + \alpha |T|$$

when

$$\alpha \in [\alpha_\ell, \alpha_{\ell+1}) \subseteq [0, +\infty) \quad \ell = 1, 2, \dots, L$$

# Pruning...

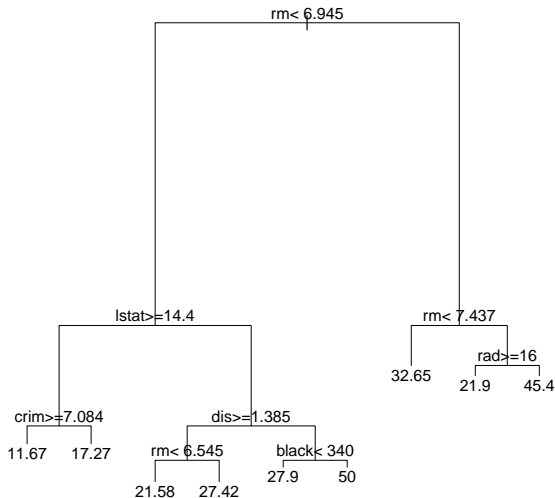
- Split the data into  $K$  folds
- For  $j = 1, \dots, K$ 
  - Build a tree without the  $j$ -th fold
  - Prune it with  $\alpha_\ell$ ,  $\ell = 1, \dots, L$
  - Predict  $j$ -th fold with these  $L$  trees
  - Record the prediction errors.
- Average over the folds.
- We obtain  $K$ -fold CV-estimated prediction errors for the  $L$  trees corresponding to pruning with  $\alpha_\ell$ ,  $\ell = 1, \dots, L$ .

# Boston Example

Pruning works...

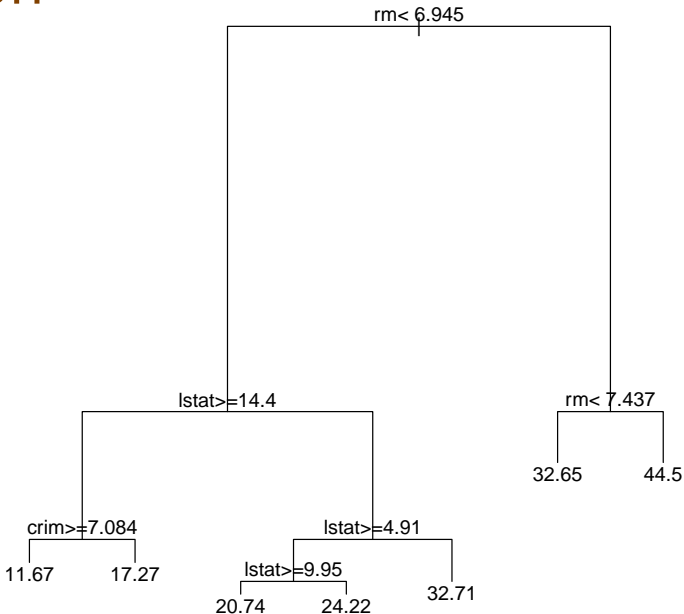
```
> b <- ***cp with minimum xerror***  
>  
> bos.t3 <- prune(bos.to, cp=b)  
> plot(bos.t3)  
> pr.t3 <- predict(bos.t3,  
                    newdata=dat.te,  
                    type='vector')  
> with(dat.te, mean((medv - pr.t3)^2))  
[1] 18.96988
```

# Pruned tree





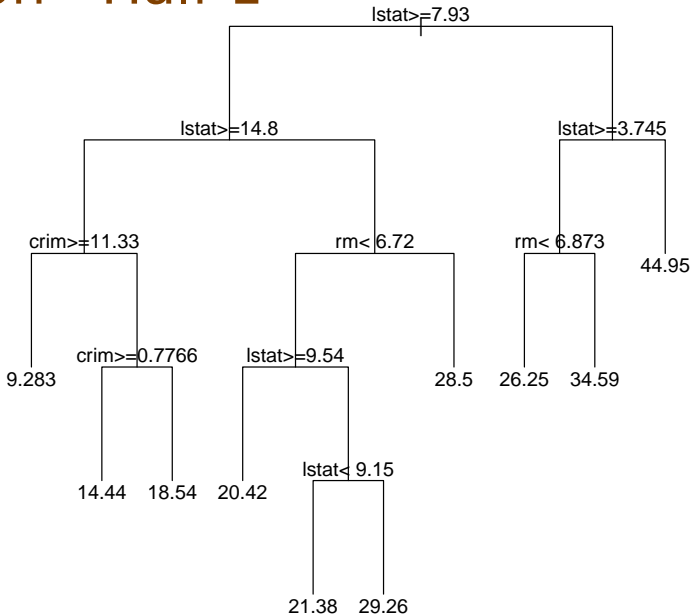
# Boston



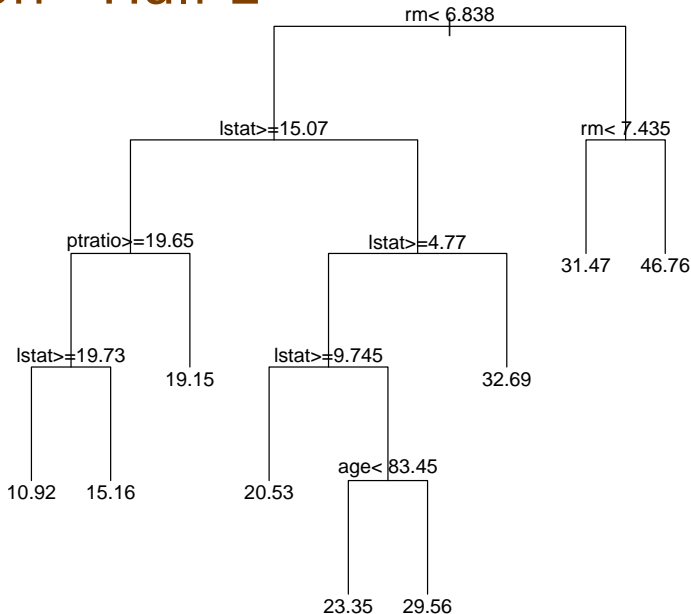
# Bagging

- Trees can be highly variable
- Trees computed on samples from the sample population can be quite different from each other
- For example, we split the Boston data in two...

# Boston - Half 1



# Boston - Half 2



# Bagging

- Linear regression, for example, is not so variable
- Estimated coefficients computed on the same two halves

```
(Intercept)  crim    zn  indus  chas
[1,]          39.21 -0.13  0.04   0.04  2.72
[2,]          33.12 -0.10  0.05  -0.01  2.80

      nox    rm  age    dis  rad    tax
[1,]   -20.07  3.45   0  -1.44  0.28 -0.01
[2,]   -14.18  4.15   0  -1.46  0.34 -0.02

      ptratio  black  lstat
[1,]   -1.01   0.01 -0.56
[2,]   -0.90   0.01 -0.50
```

# Bagging

- If we could average many trees trained on independent samples from the same population, we would obtain a predictor with lower variance
- If  $\hat{f}_1, \hat{f}_2, \dots, \hat{f}_B$  are  $B$  regression trees, then their average is

$$\hat{f}_{\text{av}}(\mathbf{x}) = \frac{1}{B} \sum_{j=1}^B \hat{f}_j(\mathbf{x})$$

# Bagging

- However, we generally do not have  $B$  training sets...
- We can **bootstrap** the training set to obtain  $B$  pseudo-new-training sets
- Let  $(Y_1, \mathbf{X}_1), (Y_2, \mathbf{X}_2), \dots, (Y_n, \mathbf{X}_n)$  be the training sample, where

$$(Y_j, \mathbf{X}_j) \sim F_0$$

# Bagging

- If we knew  $F_0$ , then we could generate / simulate new training sets, and average the resulting trees...
- We do not know  $F_0$ , but we have an estimate for it
- Let  $F_n$  be the empirical distribution of our only training set  $(Y_1, \mathbf{X}_1), (Y_2, \mathbf{X}_2), \dots, (Y_n, \mathbf{X}_n)$



# Bagging

- We know that

$$F_n \xrightarrow{n \rightarrow \infty} F_0$$

(in what sense?)

- Bootstrap generates / simulates samples from  $F_n$
- Taking a sample of size  $n$  from  $F_n$  is the same as sampling with replacement from the training set  $(Y_1, \mathbf{X}_1), (Y_2, \mathbf{X}_2), \dots, (Y_n, \mathbf{X}_n)$