

k	CP	ADJUSTED R SQUARE	97 cases R SQUARE	after deleting the 2 outliers RESID SS	MODEL VARIABLES
1	903.5	0.0000	0.0000	183.102	INTERCEPT ONLY
2	0.7	0.9052	0.9062	17.1785	B
2	406.6	0.4944	0.4996	91.6174	A
2	426.0	0.4748	0.4802	95.1708	C
3	2.1	0.9048	0.9068	17.0741	A C
3	2.6	0.9043	0.9063	17.1654	B C
3	2.6	0.9042	0.9062	17.1678	A B
4	4.0	0.9039	0.9069	17.0539	A B C

1) The output above is from software that does all subsets variable selection. The data is from Ashworth (1842). The predictors were A = log(1692 property value), B = log(1841 property value) and C = log(percent increase in value) while the response variable is Y = log(1841 population). All models contain an intercept=constant. Find model  $I_I$  that has the fewest number of predictors such that  $C_p(I_I) \leq C_p(I_{min}) + 1$ . This model is the initial model to examine.

Base terms: Intercept					
	df	RSS		k	C_I
Add: log[D]	29	0.383244		2	30.860
Add: log[Ht]	29	4.81297		2	699.629
Base terms: (log[D])					
	df	RSS		k	C_I
Add: log[Ht]	28	0.185463		3	3.000

2) The above output is for 31 black cherry trees.  $D$  = diameter of the tree 4.5 feet of the ground in inches,  $Ht$  = height of the tree in feet,  $Vol$  = marketable volume of wood in cubic feet.  $Y = \log(Vol)$  is the response variable while  $\log(D)$  and  $\log(Ht)$  are possible predictors. All models have a constant. From the above output, what model should be used? Do not forget the constant.

3) Suppose  $\mathbf{Y}^* = \mathbf{X}\hat{\boldsymbol{\beta}} + \mathbf{r}^W$  where where  $E(\mathbf{r}^W) = \mathbf{0}$  and  $Cov(\mathbf{r}^W) = Cov(\mathbf{Y}^*) = MSE \mathbf{I}_n$ . Then  $\hat{\boldsymbol{\beta}}^* = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y}^*$ . Recall that  $\mathbf{X}$  is an  $n \times p$  constant matrix. Simplify quantities when possible.

a) What is  $E(\hat{\boldsymbol{\beta}}^*)$ ?

b) What is  $Cov(\hat{\boldsymbol{\beta}}^*)$ ?

c) Recall that  $\mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{P}\mathbf{Y}$ . What is  $E(\hat{\boldsymbol{\beta}}_I^*) = E[(\mathbf{X}_I^T \mathbf{X}_I)^{-1} \mathbf{X}_I^T \mathbf{Y}^*]$ ?

d) What is  $Cov(\hat{\boldsymbol{\beta}}_I^*)$ ?