## MLR model selection process 1

Here is a schematic example to illustrate the backwards elimination process of MLR model selection: It starts with the full model.

Suppose the full MLR model consists of 4 predictors. Thus, it looks like

$$
\hat{y}=b_{0}+b_{1} x_{1}+b_{2} x_{2}+b_{3} x_{3}+b_{4} x_{4}
$$

The software output will tell us the adjusted $R^{2}$ for this model.
Step 1: Recompute the model after dropping one variable at time, and check the new adjusted $R^{2}$.

| $x_{1}$ | $x_{2}$ | $x_{3}$ | $x_{4}$ | new adj $R^{2}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\downarrow$ |
| $\checkmark$ | $\times$ | $\checkmark$ | $\checkmark$ | $\uparrow$ |
| $\checkmark$ | $\checkmark$ | $\times$ | $\checkmark$ | $\downarrow$ |
| $\checkmark$ | $\checkmark$ | $\checkmark$ | $\times$ | $\downarrow$ |

In this example when $x_{2}$ is dropped, adjusted $R^{2}$ goes up. Thus, we drop $x_{2}$ from the model.

Step 2: Repeat the process - drop one variable at time, and check the adjusted $R^{2}$.

| $x_{1}$ | $x_{3}$ | $x_{4}$ | new adj $R^{2}$ |
| :---: | :---: | :---: | :---: |
| $\times$ | $\checkmark$ | $\checkmark$ | $\downarrow$ |
| $\checkmark$ | $\times$ | $\checkmark$ | $\downarrow$ |
| $\checkmark$ | $\checkmark$ | $\times$ | $\uparrow$ |

We drop $x_{4}$ from the model, since it causes adjusted $R^{2}$ to go up.
Step 3: Repeat the process - drop one variable at time, and check the adjusted $R^{2}$.

| $x_{1}$ | $x_{3}$ | new adj $R^{2}$ |
| :---: | :---: | :---: |
| $\times$ | $\checkmark$ | $\downarrow$ |
| $\checkmark$ | $\times$ | $\downarrow$ |

Conclusion: The remaining predictors ( $x_{1}$ and $x_{3}$ ) comprise the optimal model, since dropping either of them will decrease the adjusted $R^{2}$.

## MLR model selection process 2

Here is a schematic example to illustrate the forward selection process of MLR model selection: It starts with no predictors in the model. Thus, it looks like:

$$
\hat{y}=b_{0}
$$

Step 1: Compute the model after adding one predictor at a time, and check the adjusted $R^{2}$. For example, here is what it might look like:

|  | adj $R^{2}$ |
| :---: | :---: |
| $x_{1}$ | 56.3 |
| $x_{2}$ | 35.1 |
| $x_{3}$ | 59.5 |
| $x_{4}$ | 14.7 |

Since $x_{3}$ has the largest $R^{2}$, we include it in the model.
Step 2: Repeat the process - add one (of the remaining) predictors at a time and check the adjusted $R^{2}$.

|  | adj $R^{2}$ |
| :---: | :---: |
| $x_{1}+x_{3}$ | 64.7 |
| $x_{2}+x_{3}$ | 45.4 |
| $x_{4}+x_{3}$ | 14.7 |

We add $x_{1}$ to the model, since it increases the adjusted $R^{2}$ the most.
Step 3: Repeat the process - add one (of the remaining) predictors at a time and check the adjusted $R^{2}$.

|  | adj $R^{2}$ |
| :---: | :---: |
| $x_{2}+\left(x_{1}+x_{3}\right)$ | 52.1 |
| $x_{4}+\left(x_{1}+x_{3}\right)$ | 34.9 |

Conclusion: None of the remaining predictors increases the adjusted $R^{2}$. So the optimal model consists of the predictors $x_{1}$ and $x_{3}$.

