Multiple Linear Regression

Example: Diabetes Data.

In the SPSS parameterization:

 β_{30}, β_{31} Group 3 Intercept and Slope

 $\begin{array}{ll} \beta_{10}=\beta_{30}+\delta_{10} & \mbox{Changes in the Intercepts in} \\ \beta_{20}=\beta_{30}+\delta_{20} & \mbox{Groups 1 and 2 are } \delta_{10} \mbox{ and } \delta_{20} \end{array}$

 $\begin{aligned} \beta_{11} &= \beta_{31} + \delta_{11} & \text{Changes in the Slopes in} \\ \beta_{21} &= \beta_{31} + \delta_{21} & \text{Groups 1 and 2 are } \delta_{11} \text{ and } \delta_{21} \end{aligned}$

Thus the six new parameters are

 $\beta_{30}, \beta_{31}, \delta_{10}, \delta_{20}, \delta_{11}, \delta_{21}$

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$$\begin{array}{ll} \text{MODEL 0} & \beta_{31} = 0 \\ & \delta_{10} = \delta_{20} = \delta_{11} = \delta_{21} = 0 \end{array}$$

$$\begin{array}{ll} \text{MODEL 1} & \beta_{31} = \delta_{11} = \delta_{21} = 0 \\ & \text{MODEL 2} & \delta_{10} = \delta_{20} = \delta_{11} = \delta_{21} = 0 \\ & \text{MODEL 3} & \delta_{11} = \delta_{21} = 0 \end{array}$$

$$\begin{array}{l} \text{MODEL 3} & \delta_{11} = \delta_{21} = 0 \\ & \text{Note: } \beta_{31} = 0 \Longrightarrow \delta_{11} = \delta_{21} = 0, \text{ as } X_1 \text{ is not included in the model.} \end{array}$$

Counting Parameters

Simple Linear Regression

Multiple Linear Regressior

- Whenever we remove a continuous covariate, from a model, we set one parameter to zero.
- ► Whenever we remove a factor predictor with *L* levels from a model, we set *L* − 1 parameters to zero.
- ► Whenever we remove a two-way interaction between these variables from a model, we set 1.(L 1) = L 1 parameters to zero.

Multiple Linear Regression Models 0,1,2,3 are nested inside Model 4.

Two approaches to finding the best model are used:

- 1. Start with Model 0 and try to **add** terms that improve the model fit (**Forward Selection**)
- 2. Start with Model 4 and try to remove terms that improve the model fit (**Backward Selection**)

Note: Models 0,1 and 2 are nested inside Model 3. Model 0 is nested inside Models 1 and 2. Therefore we can begin with Model 4, or Model 3 or Model 1 or 2, and simplify to a nested model.

Multiple Linear Regression

Example: Diabetes Data.

Here n = 144. From SPSS output handouts:

Model	Description	SSE	р
0	1	28.504	1
1	X_2	4.160	3
2	X_1	3.738	2
3	$X_1 + X_2$	1.472	4
4	$X_1 + X_2 + X_1 \cdot X_2$	1.318	6

p is the number of non-zero parameters; k or g is always p-1 in the following analysis.

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Backward Selection:

Complete Model : Model 4 Reduced Model : Model 3

Here
$$k = 5, g = 3$$
 so $k - g = 2$, and $n - k - 1 = 144 - 5 - 1 = 138$.

$$F = \frac{(SSE_R - SSE_C)/(k - g)}{SSE_C/(n - k - 1)} = \frac{(1.472 - 1.318)/2}{1.318/138} = 8.062$$

We compare this with the

$$\mathsf{Fisher}\mathsf{-F}(k-g,n-k-1) = \mathsf{Fisher}\mathsf{-F}(2,138)$$

distribution; we have $F_{\alpha}(2, 138) = 3.061$, so we

Reject
$$H_0$$
 at $\alpha = 0.05$

Multiple Linear Regression

i.e. Model 4 $(X_1 + X_2 + X_1 X_2)$ fits significantly better than Model 3 $(X_1 + X_2)$.

- we cannot simplify the complete model to the reduced model without the loss of significant explanatory power.

The Interaction is Necessary in the Model

Backward selection stops here; we cannot simplify further from the complete model.