• remove non-significant explanatory variables;
• group together factor levels that do not differ from one another;
• in ANCOVA, set non-significant slopes of continuous explanatory variables to zero.

All the above are subject, of course, to the caveats that the simplifications make good scientific sense and do not lead to significant reductions in explanatory power.

Just as there is no perfect model, so there may be no optimal scale of measurement for a model. Suppose, for example, we had a process that had Poisson errors with multiplicative effects amongst the explanatory variables. Then, one must choose between three different scales, each of which optimizes one of three different properties:

• the scale of $\sqrt{y}$ would give constancy of variance;
• the scale of $y^{2/3}$ would give approximately normal errors;
• the scale of $\ln(y)$ would give additivity.

Thus, any measurement scale is always going to be a compromise, and you should choose the scale that gives the best overall performance of the model.

**Steps Involved in Model Simplification**

There are no hard and fast rules, but the procedure laid out in Table 9.2 works well in practice. With large numbers of explanatory variables, and many interactions and non-linear terms, the process of model simplification can take a very long time. But this is time

**Table 9.2.** Model simplification process.

<table>
<thead>
<tr>
<th>Step</th>
<th>Procedure</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Fit the maximal model</td>
<td>Fit all the factors, interactions and covariates of interest. Note the residual deviance. If you are using Poisson or binomial errors, check for overdispersion and rescale if necessary.</td>
</tr>
<tr>
<td>2</td>
<td>Begin model simplification</td>
<td>Inspect the parameter estimates using the R function <code>summary</code>. Remove the least significant terms first, using <code>update -</code>, starting with the highest-order interactions.</td>
</tr>
<tr>
<td>3</td>
<td>If the deletion causes an insignificant increase in deviance</td>
<td>Leave that term out of the model. Inspect the parameter values again. Remove the least significant term remaining.</td>
</tr>
<tr>
<td>4</td>
<td>If the deletion causes a significant increase in deviance</td>
<td>Put the term back in the model using <code>update +</code>. These are the statistically significant terms as assessed by deletion from the maximal model.</td>
</tr>
<tr>
<td>5</td>
<td>Keep removing terms from the model</td>
<td>Repeat steps 3 or 4 until the model contains nothing but significant terms. This is the minimal adequate model. If none of the parameters is significant, then the minimal adequate model is the null model.</td>
</tr>
</tbody>
</table>
well spent because it reduces the risk of overlooking an important aspect of the data. It is important to realize that there is no guaranteed way of finding all the important structures in a complex dataframe.

Caveats

Model simplification is an important process but it should not be taken to extremes. For example, care should be taken with the interpretation of deviances and standard errors produced with fixed parameters that have been estimated from the data. Again, the search for ‘nice numbers’ should not be pursued uncritically. Sometimes there are good scientific reasons for using a particular number (e.g. a power of 0.66 in an allometric relationship between respiration and body mass). It is much more straightforward, for example, to say that yield increases by 2 kg per hectare for every extra unit of fertilizer, than to say that it increases by 1.947 kg. Similarly, it may be preferable to say that the odds of infection increase 10-fold under a given treatment, than to say that the logits increase by 2.321; without model simplification this is equivalent to saying that there is a 10.186-fold increase in the odds. It would be absurd, however, to fix on an estimate of 6 rather than 6.1 just because 6 is a whole number.

Order of deletion

The data in this book fall into two distinct categories. In the case of planned experiments, all of the treatment combinations are equally represented and, barring accidents, there are no missing values. Such experiments are said to be orthogonal. In the case of observational studies, however, we have no control over the number of individuals for which we have data, or over the combinations of circumstances that are observed. Many of the explanatory variables are likely to be correlated with one another, as well as with the response variable. Missing treatment combinations are commonplace, and the data are said to be non-orthogonal. This makes an important difference to our statistical modelling because, in orthogonal designs, the variation that is attributed to a given factor is constant, and does not depend upon the order in which factors are removed from the model. In contrast, with non-orthogonal data, we find that the variation attributable to a given factor does depend upon the order in which factors are removed from the model. We must be careful, therefore, to judge the significance of factors in non-orthogonal studies, when they are removed from the maximal model (i.e. from the model including all the other factors and interactions with which they might be confounded). Remember that, for non-orthogonal data, order matters.

Also, if your explanatory variables are correlated with each other, then the significance you attach to a given explanatory variable will depend upon whether you delete it from a maximal model or add it to the null model. If you always test by model simplification then you won’t fall into this trap.

The fact that you have laboured long and hard to include a particular experimental treatment does not justify the retention of that factor in the model if the analysis shows it to have no explanatory power. ANOVA tables are often published containing a mixture of significant and non-significant effects. This is not a problem in orthogonal designs, because sums of squares can be unequivocally attributed to each factor and interaction term. But as soon as there are missing values or unequal weights, then it is impossible to tell how the parameter estimates and standard errors of the significant terms would have been altered if the non-significant terms had been deleted. The best practice is as follows: