Minitab Tutorial for One-way ANOVA

For one-way ANOVA we have 1 dependent variable and 1 independent variable (factor) which as at least 2 levels.

Problem description

A pharmaceutical company is interested in the effectiveness of a new preparation designed to relieve arthritis pain. Three variations of the compound have been prepared for investigation, which differ according to the proportion of the active ingredients: T15 contains 15% active ingredients, T40 contains 40% active ingredients, and T50 contains 50% active ingredients. A sample of 20 patients is selected to participate in a study comparing the three variations of the compound. A control compound, which is currently available over the counter, is also included in the investigation. Patients are randomly assigned to one of the four treatments (control, T15, T40, T50) and the time (in minutes) until pain relief is recorded on each subject.

| Control	T15	T40	T50
12	20	17	14
15	21	16	13
18	22	19	12
16	19	15	14
20	20	19	11

Enter data such that the response variable is in one column and the factor is in a separate column. Such that it looks like this:
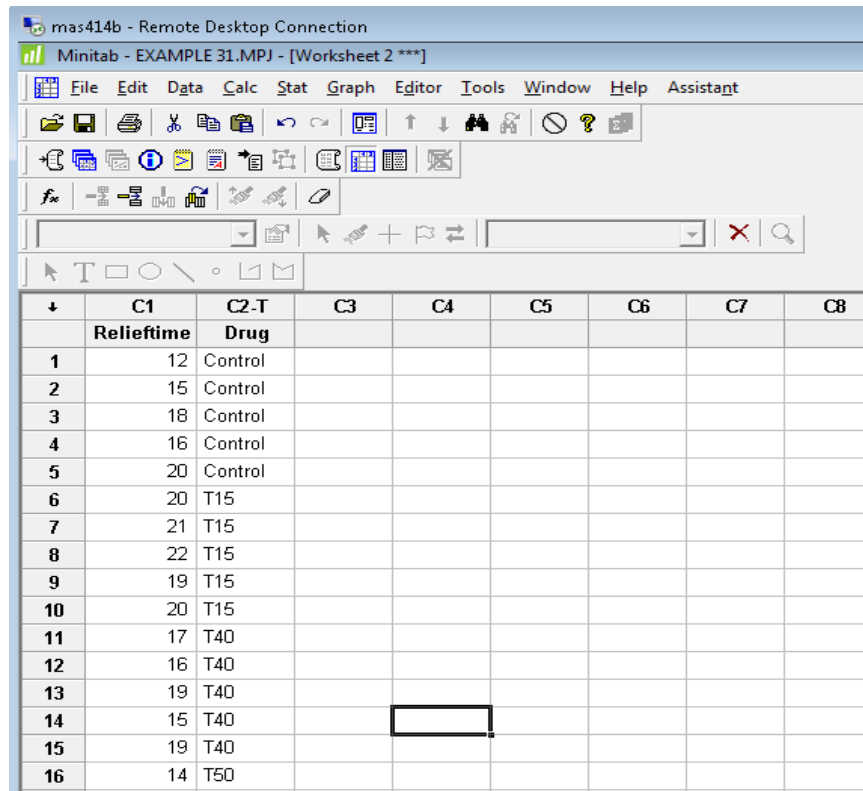
We will begin the ANOVA by assessing the necessary assumption of normality and equal variance

Normality test
1. Select **Basic Statistics➤Normality Test**
2. Your variable is **relieftime**, your dependent measure
3. Select **OK**
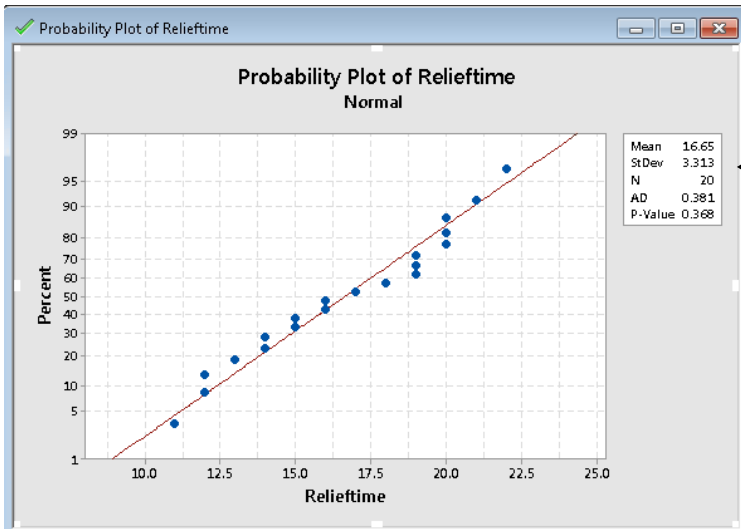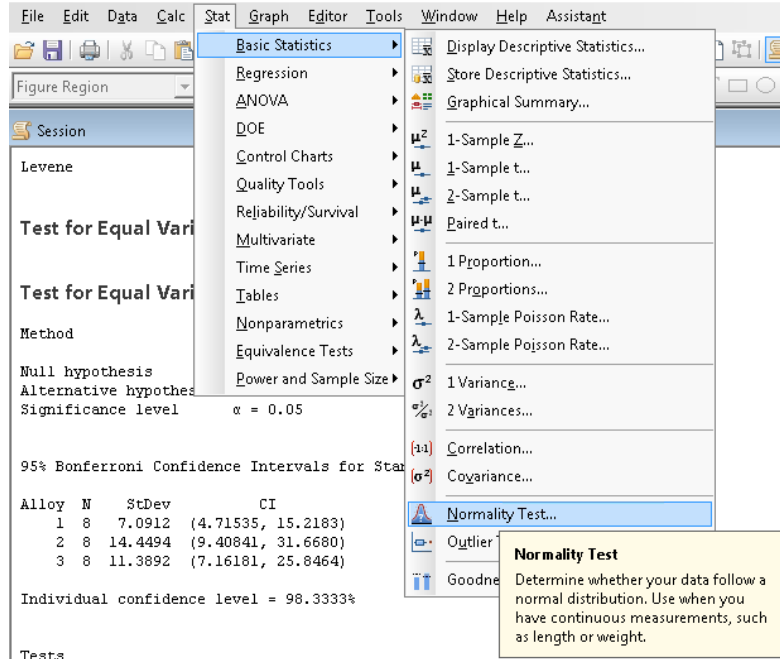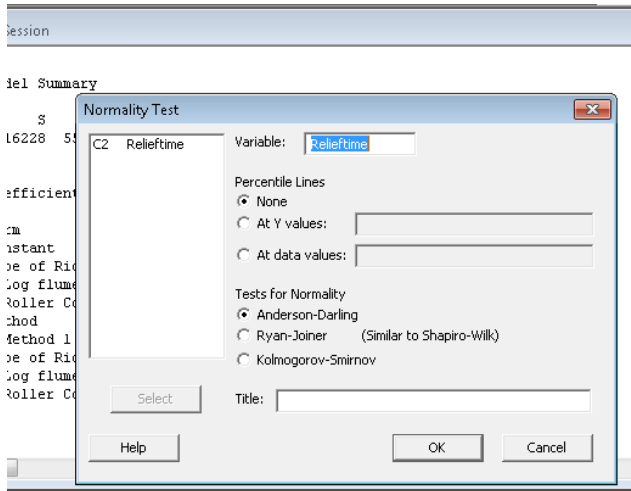
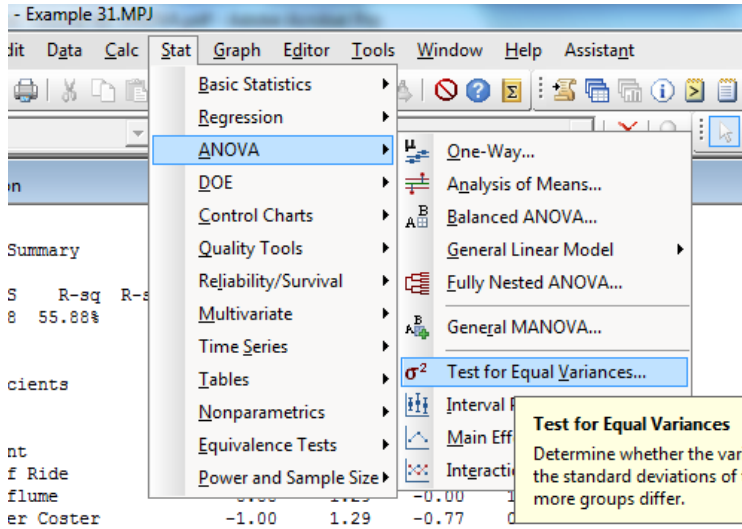The test statistic appears in the upper right hand corner of the graph

Another approach:

The population normality can be checked with a *normal probability plot of residuals*. If the distribution of residuals is normal, the plot will resemble a straight line.
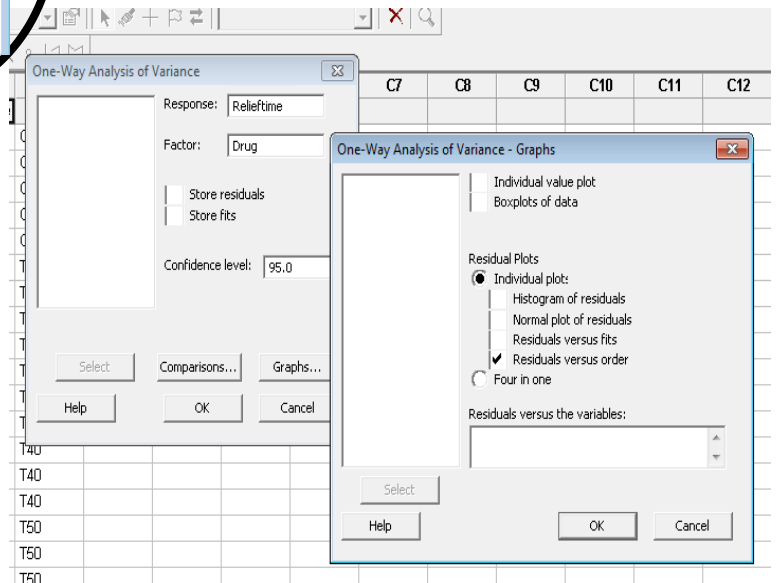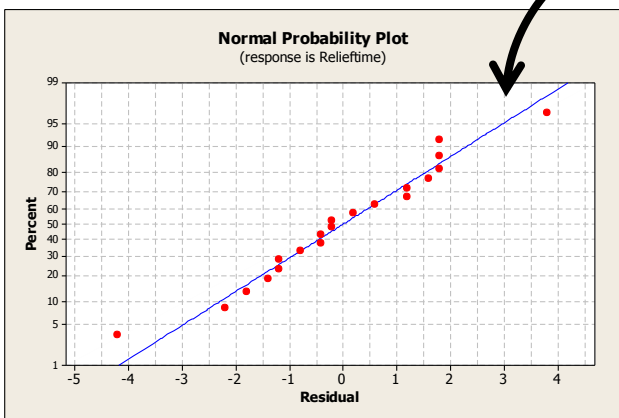
Homogeneity of Variance test
1. Select **Stat** ➤ **ANOVA** ➤ **Test for Equal Variances**

2. Again, select variables - response variable: **relieftime,** factors: **drugs**
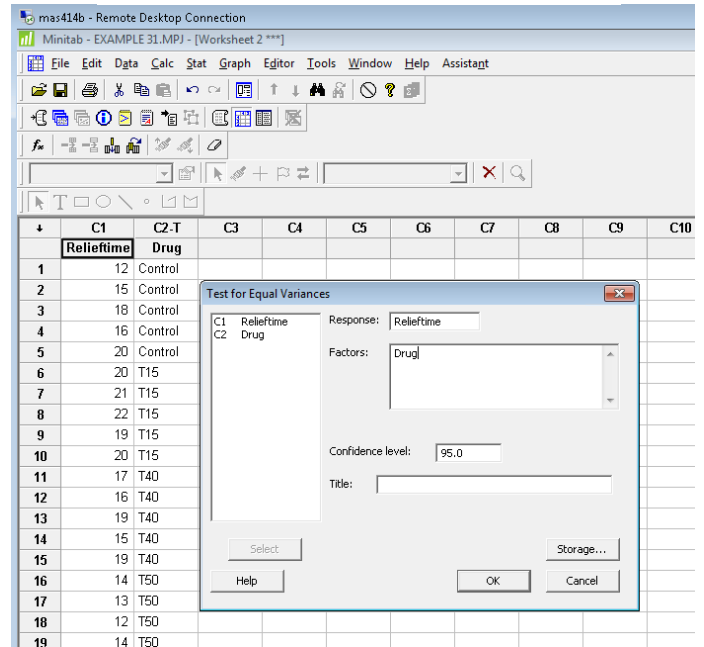
3. Select OK

The test statistic appears in the upper right hand corner of the graph

Test for Equal Variances for Relieftime

Bartlett's Test	
Test Statistic	4.41
P-Value	0.221
Levene's Test	
Test Statistic	1.47
P-Value	0.259

95% Bonferroni Confidence Intervals for StDevs
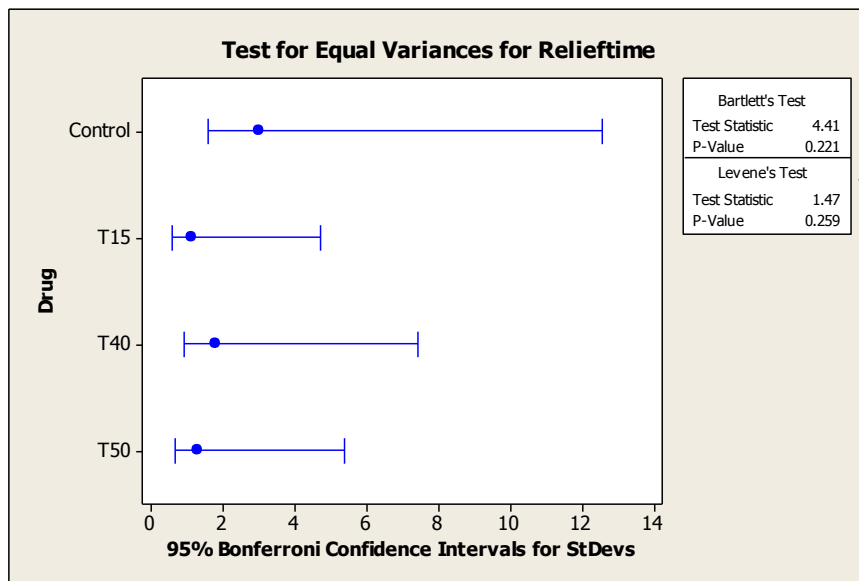
Checking Independence

The independence, especially of time related effects, can be checked with the *Residuals versus Order* (time order of data collection) plot. A positive correlation or a negative correlation means the assumption is violated. If the plot does not reveal any pattern, the independence assumption is satisfied.

\

1. Select **Stat ➤ ANOVA ➤ One Way**

2. In Response, enter relieftime. In Factor, enter drugs.
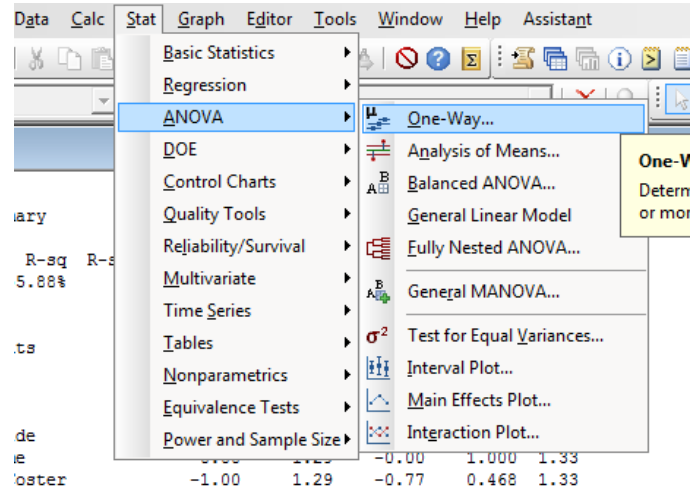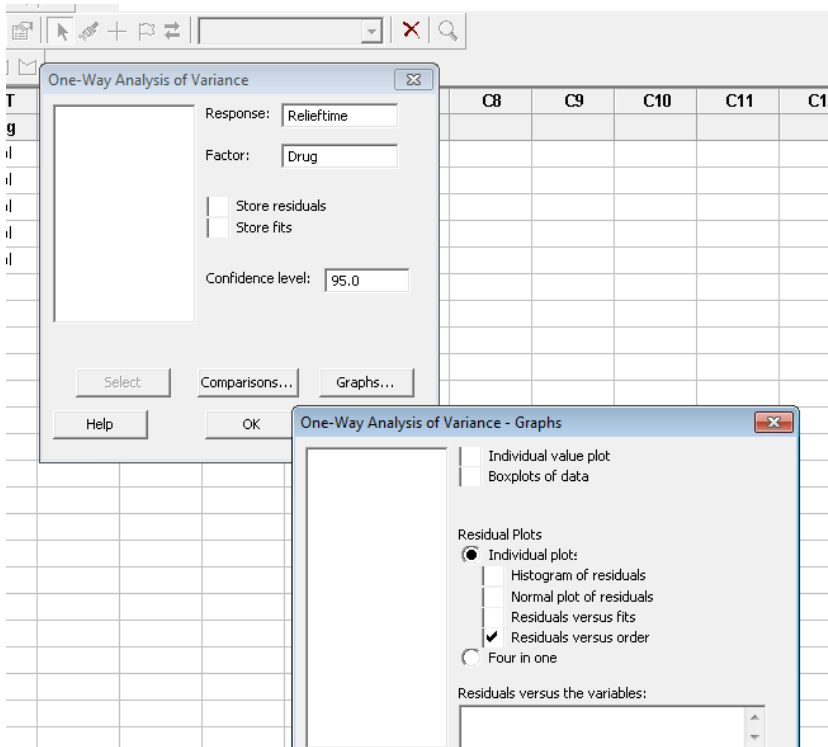
3. Select Graphs.
4. Select Residuals versus order.
5. Select **OK**
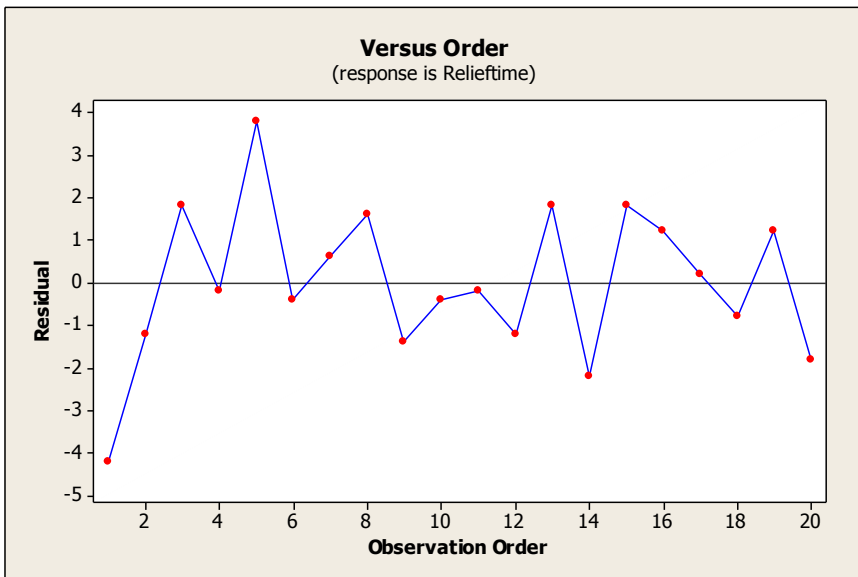
A positive correlation or a negative correlation means the assumption is violated. If the plot does not reveal any pattern, the independence assumption is satisfied.

Analysis of Variance - ANOVA
Assuming not problems with our assumptions we can continue by running the one-way ANOVA.

1. Start by going to **Stat ➤ ANOVA ➤ One Way.**

2. In Response, enter **relieftime**. In Factor, enter **drugs**.

3. Select **OK**

Output

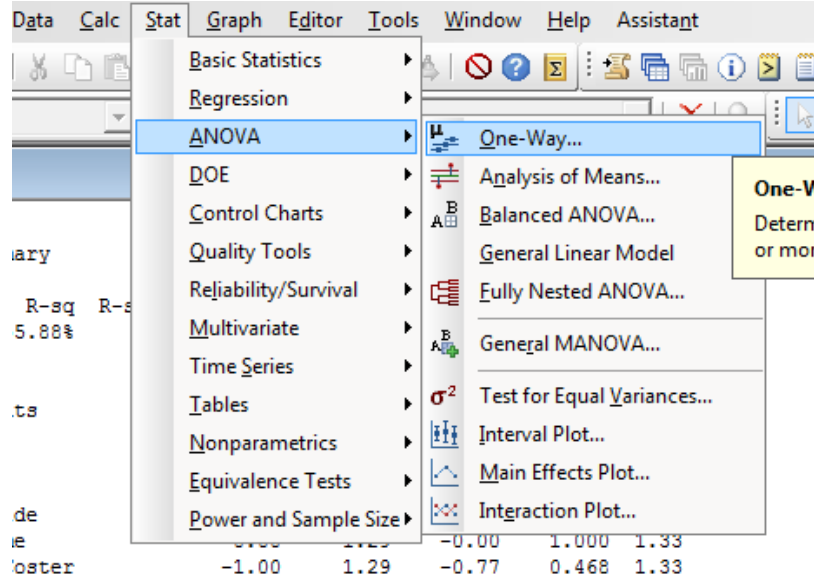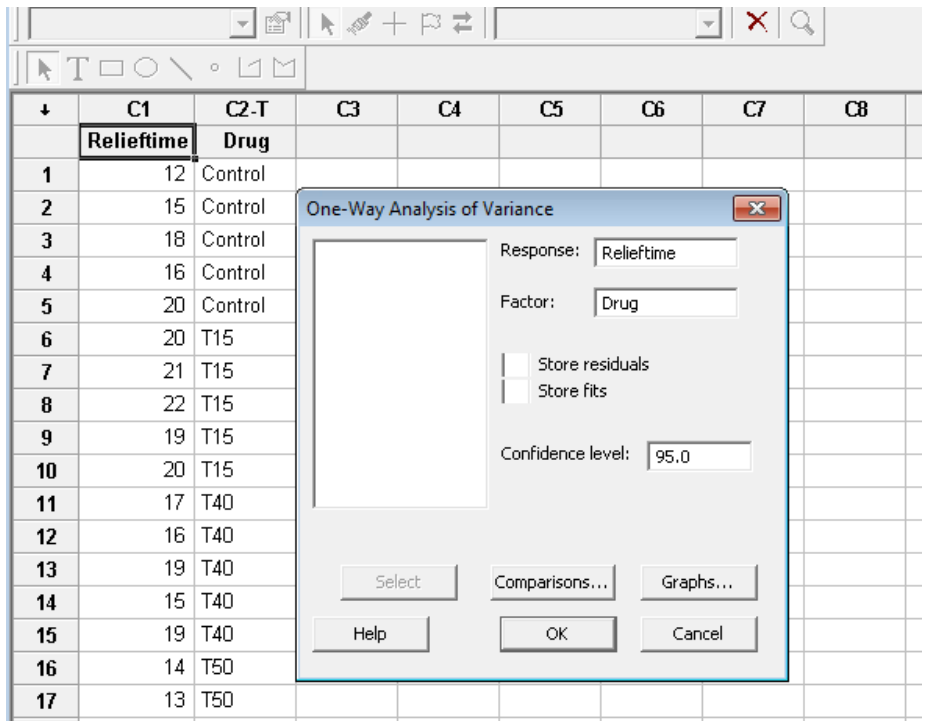Recall that the null hypothesis in ANOVA is that the means of all the groups are the same and the alternative is that at least one is different. So for our example with 4 treatment groups

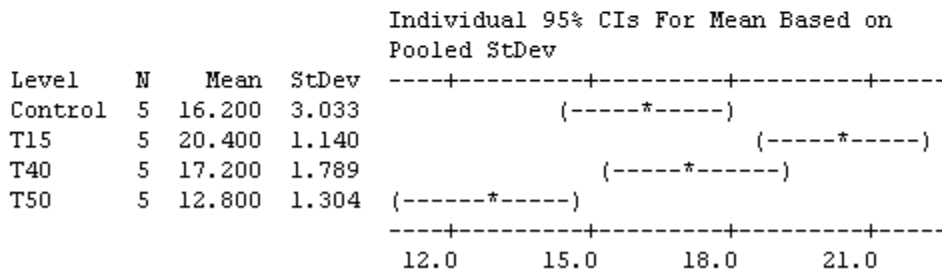$$H_o : \mu_1 = \mu_2 = \mu_3 = \mu_4$$
$$H_A : \quad \text{at least one mean is different}$$

Test for Equal Variances: Relieftime versus Drug

One-way ANOVA: Relieftime versus Drug

```
Source  DF      SS      MS      F       P
Drug     3  146.95   48.98  12.72   0.000
Error   16   61.60    3.85
Total   19  208.55

S = 1.962   R-Sq = 70.46%   R-Sq(adj) = 64.92%


                                  Individual 95% CIs For Mean Based on
                                  Pooled StDev
Level     N    Mean   StDev   ----+---------+---------+---------+-----
Control   5  16.200   3.033                 (-----*-----)
T15       5  20.400   1.140                              (-----*-----)
T40       5  17.200   1.789                   (-----*------)
T50       5  12.800   1.304   (------*-----)
                              ----+---------+---------+---------+-----
                              12.0      15.0      18.0      21.0

Pooled StDev = 1.962
```

To check the hypothesis the computer compares the value for the observed F [12.72] to the expected value for F-observed given the number of groups and the sample sizes. If this is a rare event [it will be unusually large is Ho is not true] we will reject Ho. To determine if F-observed is unusual, we need to look at the Significance of the F value [often called the P-value]. If this value is less than .05, it means that a score this large would occur less than 5% of the time [or 1 in every 20 trials] and we will consider it sufficiently rare. The smaller this value gets the rarer the score and the more certain we can be that the null hypothesis is incorrect. In the case of above example, we can be confident that if we reject the null hypothesis, there is less than a 1 in a 1000 chance that we would be incorrect. We limit ourselves to 1 in a 1000 as [Sig=.000] does not mean that the probability of getting a score this large is zero, just that it is equal to zero at three significant figures

Multiple Comparisons

Using ANOVA table we reject the null hypothesis and conclude that at least one mean is different from the others. The next question is how they are different. To answer this question:

1. Start by going to **Stat ➤ ANOVA ➤ One Way.**
2. Select Comparisons
3. Select the second option, **Fisher's, individual error rate**
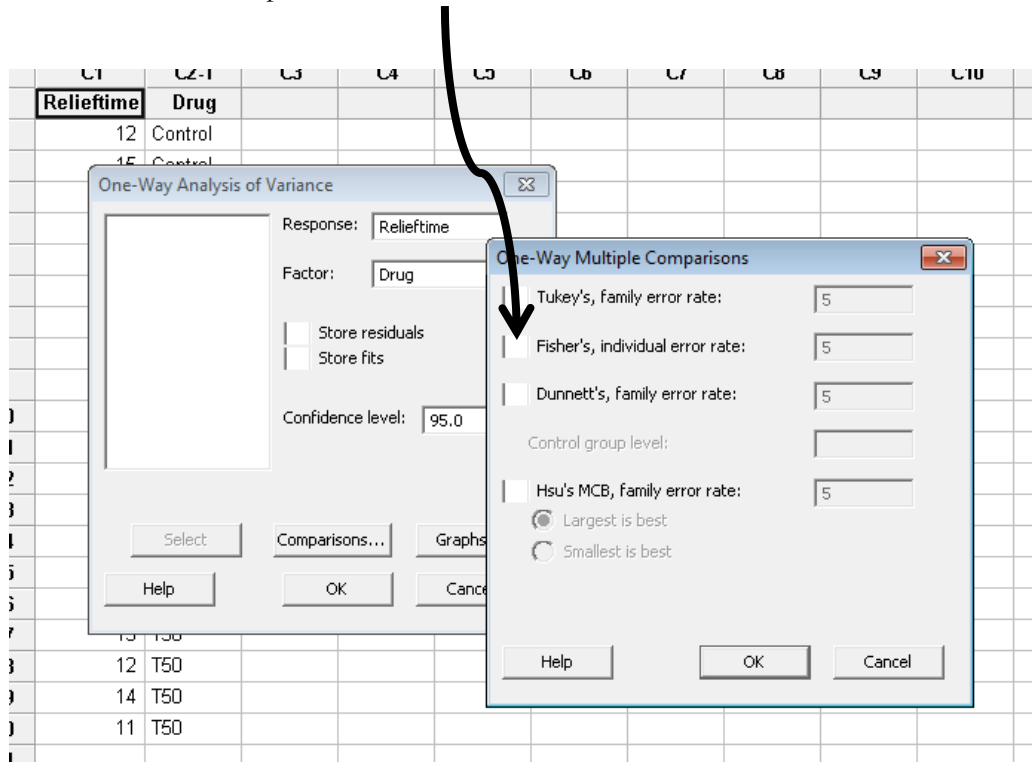
```
Grouping Information Using Fisher Method

Drug      N    Mean   Grouping
T15       5   20.400   A
T40       5   17.200       B
Control   5   16.200       B
T50       5   12.800           C

Means that do not share a letter are significantly different.


Fisher 95% Individual Confidence Intervals
All Pairwise Comparisons among Levels of Drug

Simultaneous confidence level = 81.11%


Drug = Control subtracted from:

Drug   Lower   Center   Upper   -------+---------+---------+---------+--
T15    1.569    4.200   6.831                            (---*---)
T40   -1.631    1.000   3.631                      (----*---)
T50   -6.031   -3.400  -0.769               (---*----)
                               -------+---------+---------+---------+--
                                  -6.0      0.0       6.0      12.0


Drug = T15 subtracted from:

Drug    Lower   Center    Upper   -------+---------+---------+---------+--
T40    -5.831   -3.200   -0.569                (----*---)
T50   -10.231   -7.600   -4.969   (---*----)
                                 -------+---------+---------+---------+--
                                    -6.0      0.0       6.0      12.0


Drug = T40 subtracted from:

Drug   Lower   Center   Upper   -------+---------+---------+---------+--
T50   -7.031   -4.400  -1.769        (----*---)
                               -------+---------+---------+---------+--
                                  -6.0      0.0       6.0      12.0
```
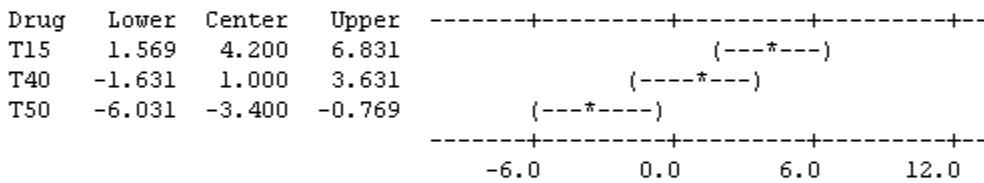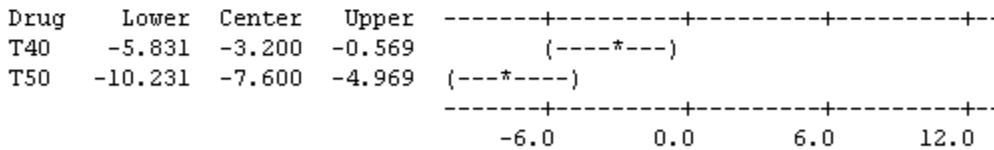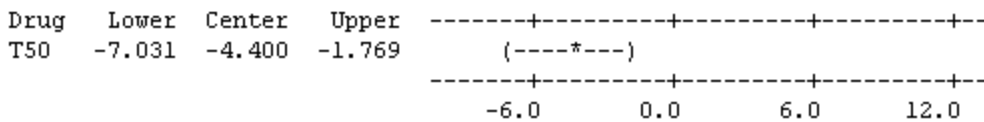
Understanding the output:

The first set of numbers provides the overall results of the test, organizing in order the different means of the groups. The letters denote statistically significant differences between the groups. The subsequent sections show the individual confidence intervals for each group.

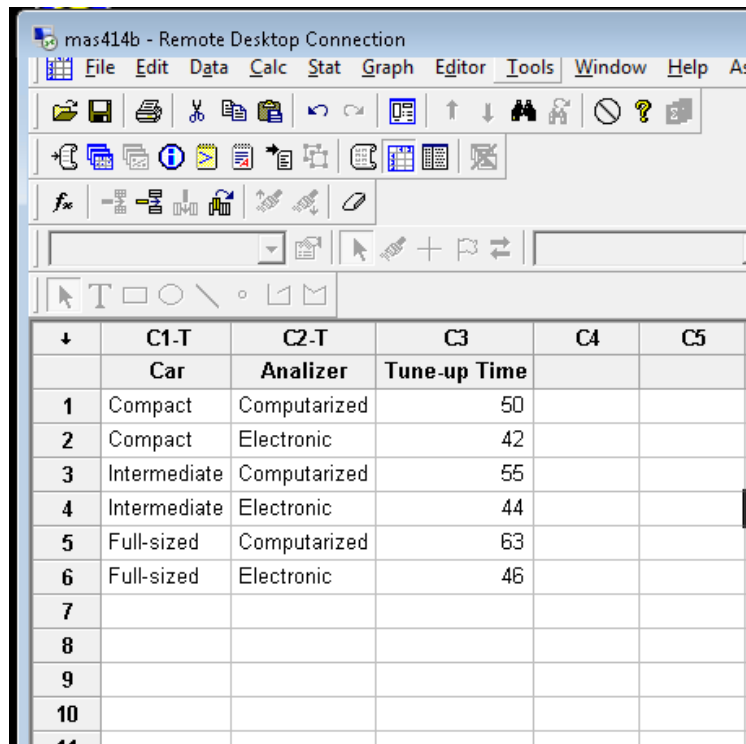# Minitab Tutorial for Randomized Block Designs

With blocking design we will always assume there is no BLOCK by TREATMENT interactions in our models (this is the assumption of **additivity**, *the treatment differences are the same for every block and the block differences are the same for every treatment*, **No interaction)**. There are several ways to check this assumption, but we will rely on a graphical evaluation. We create an interaction plot (profile plot) for block and treatment and check to see if the lines are approximately parallel. Ideally the lines would be perfectly parallel under the assumption of additivity, but as the data are random we would not expect perfect parallelism. The methods for creating the graphs for the different blocking designs are listed below

Example 24 (Chapter 13)

An automobile dealer conducted a test to determine if the time in minutes needed to complete a minor engine tune-up depends on whether a computerized engine analyzer or an electronic analyzer is used. Because a tune-up time varies among compact, intermediate, and full-sized cars, the three types of cars were used as blocks in the experiment.

RBD (1 independent variable & 1 blocking variable)

Enter data as you would with a factorial design. Place each variable in a separate column and type in the category number.
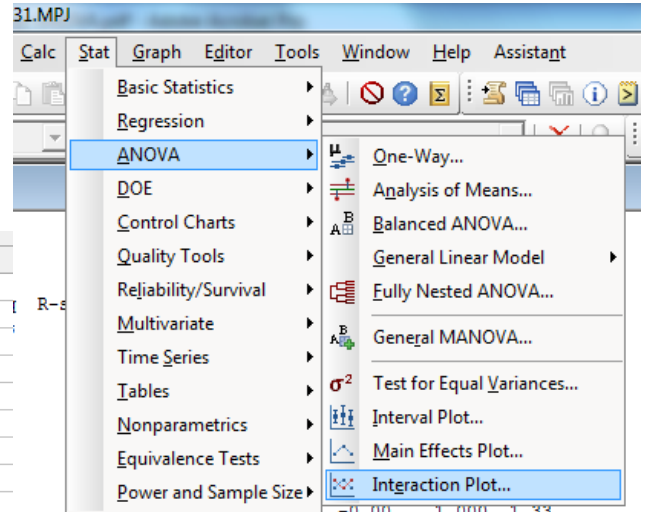
Test of Additivity Assumption

To test for additivity, you need to create an interaction plot.

1. Select **Stat ➤ ANOVA ➤ Interaction plots**

2. Select the response variable, **tune-up time** and the categorical variables, **car** and **analyzer.**
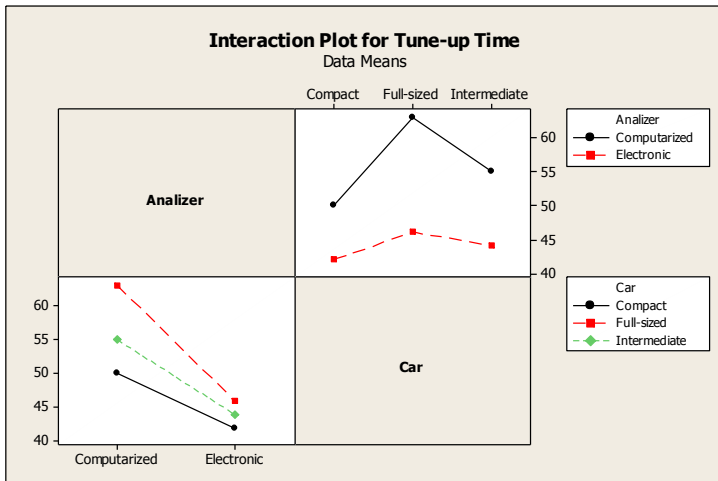   It may be helpful to select "show all interactions matrix."

Interactions Plot

| | C1 Car |
| C2 Analyzer |
| C3 Tune-up Time |

Responses:
'Tune-up Time'

Factors:
Analizer Car

☐ Display full interaction plot matrix

Select | Options...

Help | OK | Cancel

	C1-1	C2-1	C3	C4	C5	C6	C7	C8
	Car	**Analizer**	**Tune-up Time**					
1	Compact	Computarized	50					
2	Compact	Electronic	42					
3	Intermediate	Computar						
4	Intermediate	Electronic						
5	Full-sized	Computar						
6	Full-sized	Electronic						
7								
8								
9								
10								
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12								
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15								
16								
17								

31.MPJ

Calc | Stat | Graph | Editor | Tools | Window | Help | Assistant

- Basic Statistics ▸
- Regression ▸
- ANOVA ▸
  - μ One-Way...
  - Analysis of Means...
  - Balanced ANOVA...
  - General Linear Model ▸
  - Fully Nested ANOVA...
  - General MANOVA...
  - σ^2 Test for Equal Variances...
  - Interval Plot...
  - Main Effects Plot...
  - Interaction Plot...
- DOE ▸
- Control Charts ▸
- Quality Tools ▸
- Reliability/Survival ▸
- Multivariate ▸
- Time Series ▸
- Tables ▸
- Nonparametrics ▸
- Equivalence Tests ▸
- Power and Sample Size ▸

3. Select **OK**

Interpreting the graphs: The lines on the graph look approximately parallel so our assumption of additivity appears to be valid and we may continue with the analysis. We would only reject the assumption of additivity if there were dramatic evidence that the assumption was incorrect.

Interaction Plot for Tune-up Time
Data Means

Some notes that might help in grasping ANOVA interactions:

— Morning
— Evening

(a) No significant effects

(b) Significant time of day effect; no other effects

(c) Significant intensity of exercise effect; no other effect

(d) Significant intensity of exercise and time of day effects; no interaction effect

(e) Significant interaction effect; no other effects

(f) Significant time of day and interaction effects; no other effects

Sleep / Intensity of exercise / Light / Heavy

- Interaction means that the IVs are not independent. The IVs have a complex (interactive) influence on the DV.
- An interaction means that the main effects cannot be relied upon to tell the full story. When there is an interaction effect, it means the main effects do not collectively explain all of the influence of the IVs on the DV. The IVs have an interactive effect on the DV, which means the cell means must be examined for each sub-group -- this is where the nature / direction of the interaction can be found.
- Interaction is indicated by **non-parallel lines** in a line graph. In other words, if the lines are crossed or would eventually cross if extended, then there is an interaction. Of course the lines are rarely perfectly parallel, so the real question is about whether the different pattern of means across the sub-groups is to be considered unlikely to have occurred by chance. The significance test of the interaction and its associated effect size are the key pieces of information. The figure shows some possible outcomes of the experiment investigating the effects of intensity of exercise and time of day on amount of sleep

If the lines for two different groups in one factor do move in a parallel fashion, it suggests that there is a fixed difference between groups at all levels of the other factor (i.e. no interaction).
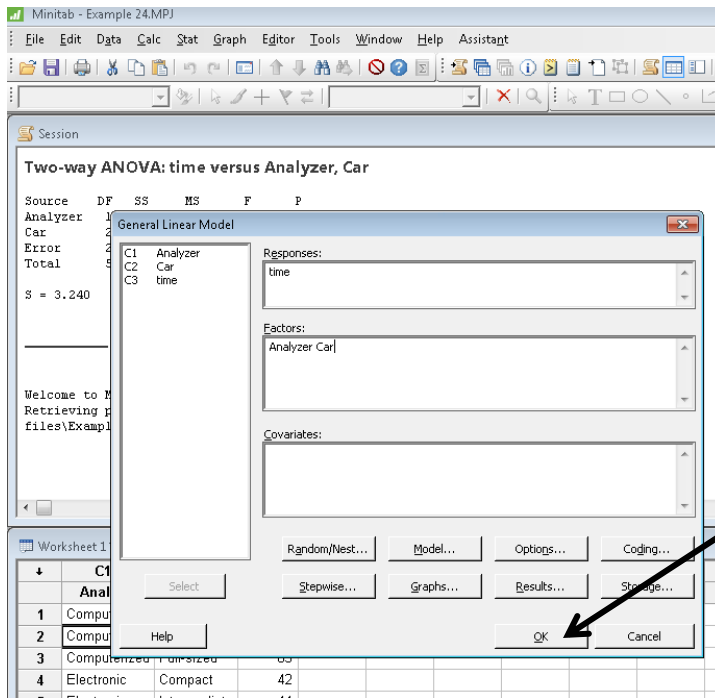
Interaction

No Interaction
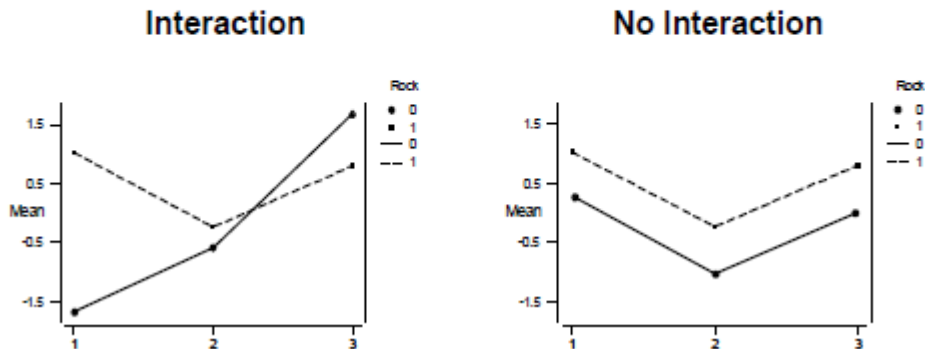
Analysis of RBD
1. Select **Stat** ➤ **ANOVA** ➤ **General Linear Model** ➤ **Fit General Model**
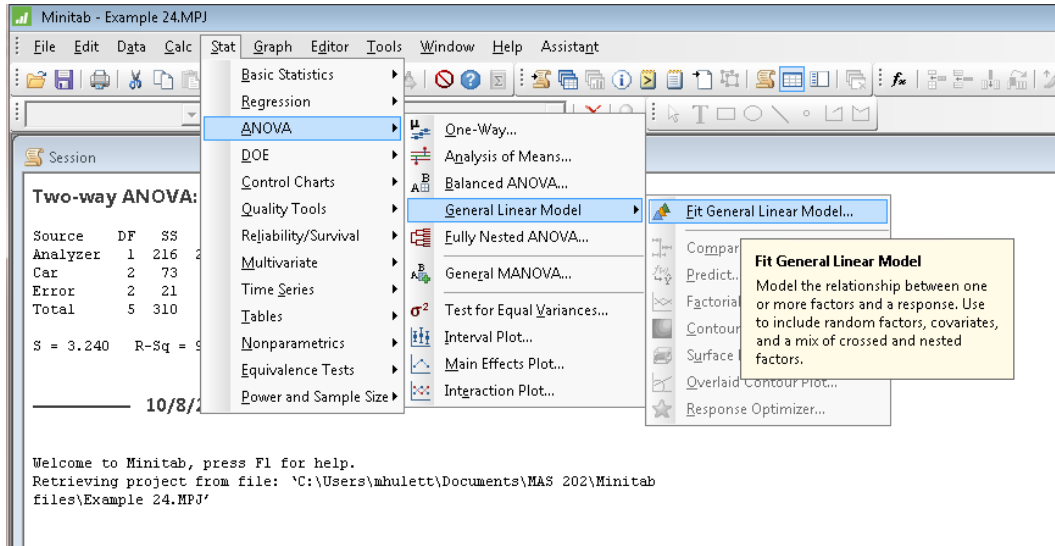
2. In response, enter **time.** In factor, **Analyzer** and **car**

3. Select **OK**

```
Analysis of Variance

Source      DF  Adj SS  Adj MS  F-Value  P-Value
  Analyzer   1  216.00  216.00    20.57    0.045
  Car        2   73.00   36.50     3.48    0.223
Error        2   21.00   10.50
Total        5  310.00
```

4. Analyze output

Because p-value is less than 0.05, we have enough evidence to conclude that not all population means are equal.
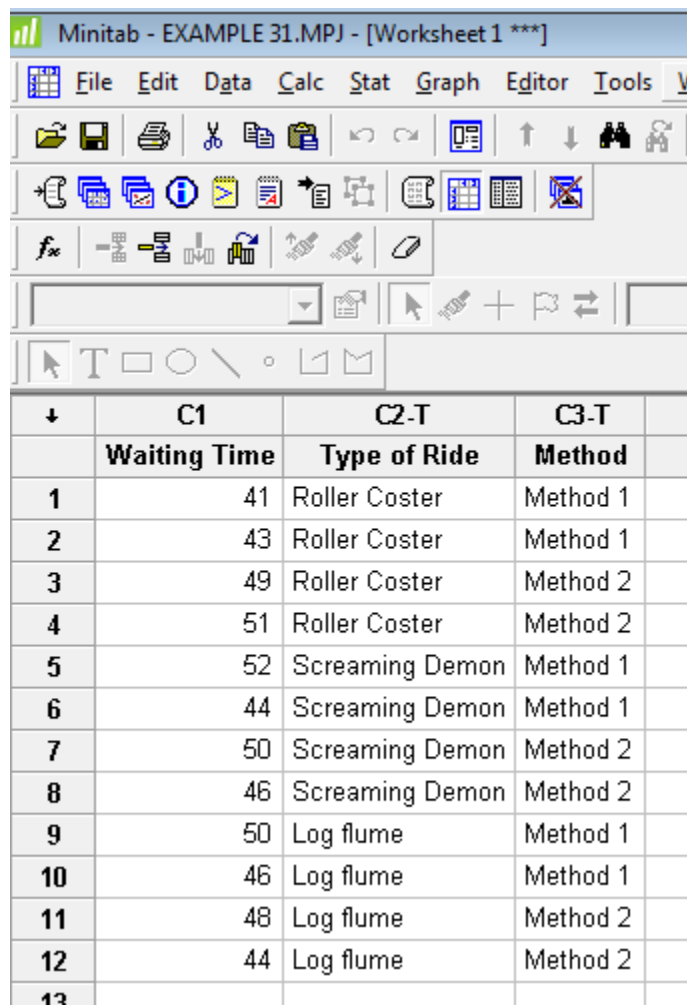
Minitab Tutorial for Factorial Experimental Design

Assuming that ANOVA assumptions are satisfied (Normality, constant variance and independence) we can continue by running the two-way ANOVA.

Example 31 (Chapter 13):
An amusement park studied methods for decreasing the waiting time (minutes) for rides by loading and unloading riders more efficiently. Two alternative loading/unloading methods have been proposed. To account for potential differences due to the type of ride and the possible interaction between the method of loading and unloading and the type of ride, a factorial experiment was designed. Use the following data to test for any significant effect due to the loading and unloading method, the type of ride, and interaction. Use 5% significance level.

Enter data such that the response variable is in one column and the factors are in separate columns. Such that it looks like this:

1. Start by going to **Stat ➤ ANOVA ➤ General Linear Model ➤ Fit General Linear Model**
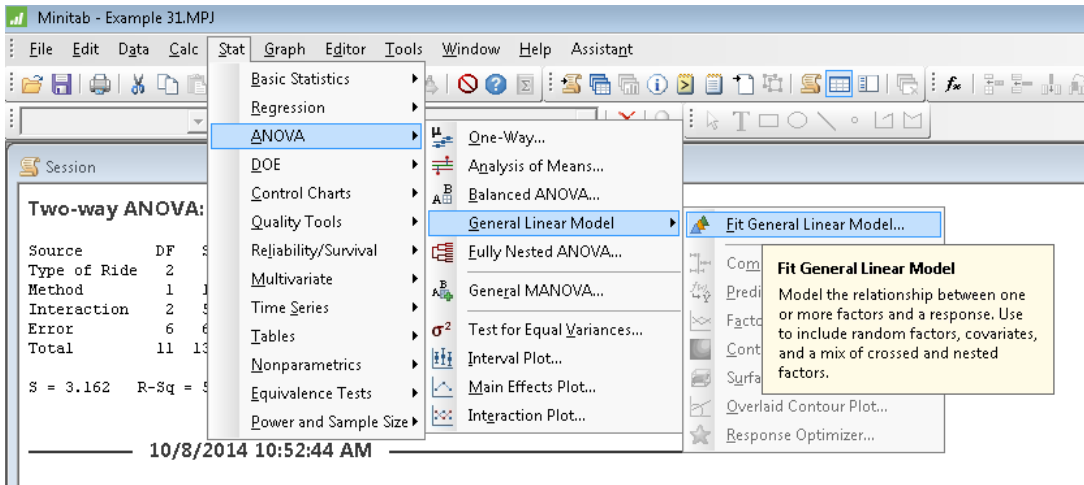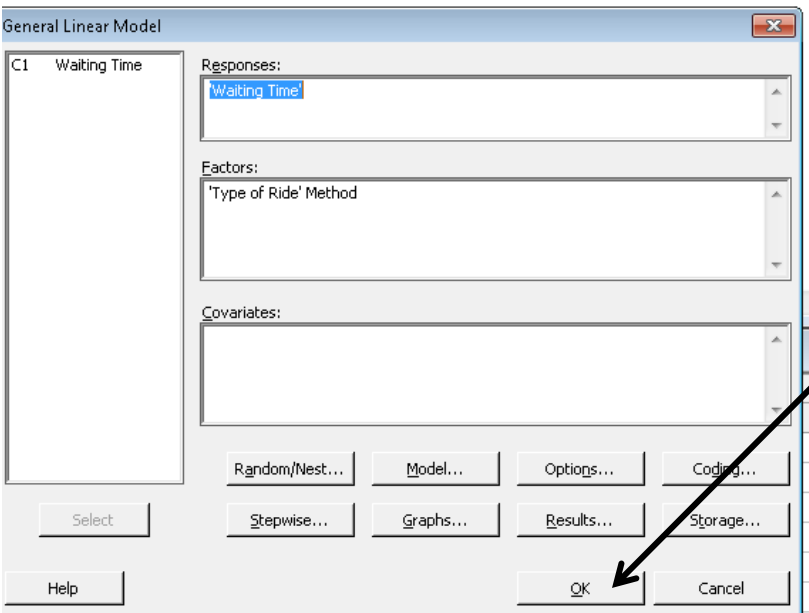

2. In Response, enter **Waiting Time**. In Factors, enter **Type of Ride** and **Method.** Select Model to add the interaction to the model.
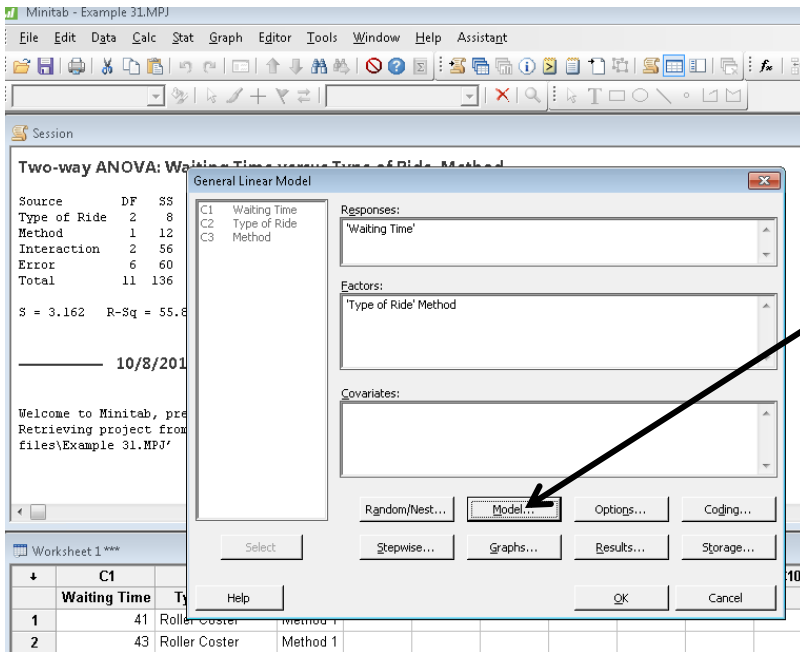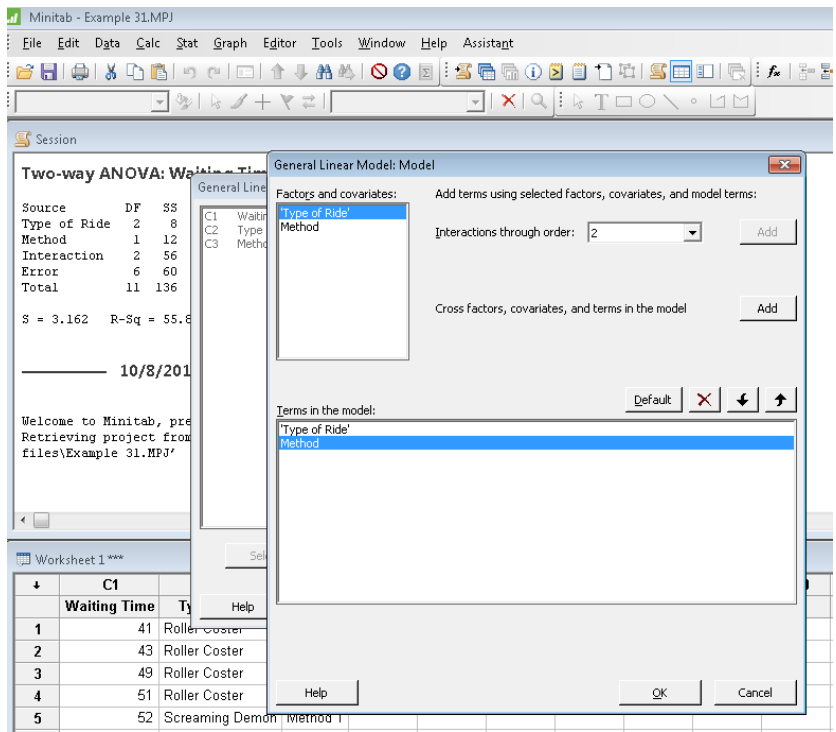
3. In Factors and covariates select one of the factors. In Terms in the model, enter the opposite factor. (This step is to add the interaction to the model)

4. Select **OK.**

5. Select **OK.**

```
Analysis of Variance

Source                DF   Adj SS   Adj MS   F-Value   P-Value
  Type of Ride         2    8.000    4.000      0.40     0.687
  Method               1   12.000   12.000      1.20     0.315
  Type of Ride*Method  2   56.000   28.000      2.80     0.138
Error                  6   60.000   10.000
Total                 11  136.000
```

Because p-values are greater than 0.05, the type of ride, method and the interaction between the factors are not significant