Assignment #9 Solutions - M. Lacey, 04/16/02

Chapter 12, Problem #3:

For a one-way analysis of variance with I=2 treatment groups, show that the F statistic is t^2 , where t is the usual t statistic for a two-sample case.

For
$$I = 2, F = \frac{SS_B / (I - 1)}{SS_w / [I(J - 1)]} = \frac{SS_B}{SS_w / [2(J - 1)]} = \frac{J[(\overline{Y}_{1.} - \overline{Y}_{..})^2 + (\overline{Y}_{2.} - \overline{Y}_{..})^2]}{\sum_{j=1}^J [(Y_{1j} - \overline{Y}_{1.})^2 + (Y_{2j} - \overline{Y}_{2.})^2] / [2(J - 1)]}$$

Since $\overline{Y}_{...} = \frac{\sum_{j=1}^{J} (Y_{1,j} + Y_{2,j})}{2J} = \frac{\overline{Y}_{1..} + \overline{Y}_{2..}}{2}, (\overline{Y}_{1..} - \overline{Y}_{...})^2 = (\frac{\overline{Y}_{1..} - \overline{Y}_{2..}}{2})^2 = (\overline{Y}_{2..} - \overline{Y}_{...})^2, \text{ and thus } SS_B = \frac{J}{2} * (\overline{Y}_{1..} - \overline{Y}_{2..})^2.$

We can also recognize that $SS_w = \sum_{j=1}^{J} \left[(Y_{1j} - \overline{Y}_{1j})^2 + (Y_{2j} - \overline{Y}_{2j})^2 \right] = (J-1)(J)(s_{\overline{Y}_{1j} - \overline{Y}_{2j}}^2).$

So
$$\frac{SS_B}{SS_w/[2(J-1)]} = \frac{J/2*(\overline{Y}_{1.}-\overline{Y}_{2.})^2}{(J-1)(J)(s_{\overline{Y}_{1.}-\overline{Y}_{2.}})/[2(J-1)]} = \frac{(\overline{Y}_{1.}-\overline{Y}_{2.})^2}{s_{\overline{Y}_{1.}-\overline{Y}_{2.}}^2}$$

To see that this is equivalent to t^2 , let $\overline{X} = \overline{Y}_1$, $\overline{Y} = \overline{Y}_2$.

Chapter 12, Problem #14:

Prove the sum of squares identity for the two-way layout: $SS_{TOT} = SS_A + SS_B + SS_{AB} + SS_E$

The outline of this proof is provided on p. 459, which begins by adding and subtracting terms to write the expression $Y_{ijk} - \overline{Y}_{...} = (Y_{ijk} - \overline{Y}_{ij.}) + (\overline{Y}_{i...} - \overline{Y}_{...}) + (\overline{Y}_{.j.} - \overline{Y}_{...}) + (\overline{Y}_{ij.} - \overline{Y}_{...} - \overline{Y}_{...})$. Squaring both sides, we get

$$\begin{split} \left(Y_{ijk} - \overline{Y}_{...}\right)^{2} &= \left[\left(Y_{ijk} - \overline{Y}_{ij.}\right) + \left(\overline{Y}_{i...} - \overline{Y}_{...}\right) + \left(\overline{Y}_{.j.} - \overline{Y}_{...}\right) + \left(\overline{Y}_{ij.} - \overline{Y}_{...} - \overline{Y}_{.j.} + \overline{Y}_{...}\right)\right]^{2} \\ &= \left(Y_{ijk} - \overline{Y}_{ij.}\right)^{2} + \left(\overline{Y}_{i...} - \overline{Y}_{...}\right)^{2} + \left(\overline{Y}_{.j.} - \overline{Y}_{...}\right)^{2} + \left(\overline{Y}_{ij.} - \overline{Y}_{...} - \overline{Y}_{...}\right)^{2} + \left(\overline{Y}_{.j.} - \overline{Y}_{...}\right)^{2} + \left(\overline{Y}_{$$

Summing over *i*, *j*, and *k* gives

$$SS_{TOT} = SS_E + SS_A + SS_B + SS_{AB} + 2\sum_i \sum_j \sum_k \left[\left(Y_{ijk} - \overline{Y}_{ij.} \right) \left(\overline{Y}_{ij.} - \overline{Y}_{...} \right) + \left(\overline{Y}_{i...} - \overline{Y}_{...} \right) \left(\overline{Y}_{ij.} - \overline{Y}_{...} \right) + \left(\overline{Y}_{.j.} - \overline{Y}_{...} \right) \left(\overline{Y}_{ij.} - \overline{Y}_{...} \right) \right]$$

To prove the identity, we must show that the remaining terms cancel out. For the first term,

$$\sum_{i} \sum_{j} \sum_{k} \left[\left(Y_{ijk} - \overline{Y}_{ij.} \right) \left(\overline{Y}_{ij.} - \overline{Y}_{...} \right) \right] = \sum_{i} \sum_{j} \left[\left(\overline{Y}_{ij.} - \overline{Y}_{...} \right) \sum_{k} \left(Y_{ijk} - \overline{Y}_{ij.} \right) \right], \text{ and since } \sum_{k} \left(Y_{ijk} - \overline{Y}_{ij.} \right) \text{ is the sum of the sum of$$

k deviations Y_{ijk} from the mean \overline{Y}_{ij} , this term is equal to 0.

Similar arguments apply demonstrate that the second and third terms are also equal to 0, and this proves the identity.

Chapter 12, Problem #19:

Analysis of worm counts in four control groups of rats.

First, we may review the descriptive statistics and look at the corresponding boxplots for the four groups:

Variab	ole	Ν	Mean	Median	StDev	
Group	1	5	290.4	303.0	57.0	
Group	2	5	323.2	286.0	67.0	
Group	3	5	274.8	282.0	68.0	
Group	4	5	371.2	346.0	60.2	
Variak	ole		Minimum	Maximum	Q1	Q3
Group	1		198.0	338.0	238.5	336.0
Group	2		265.0	412.0	270.0	395.0
Group	3		172.0	335.0	211.0	335.0
Group	4		318.0	471.0	329.0	426.0

Side-by-side boxplots (produced in MINITAB)



ANOVA table and *F*-test:

One-way Analysis of Variance

Analysis	of Var	iance			
Source	DF	SS	MS	F	P
Factor	3	27234	9078	2.27	0.119
Error	16	63954	3997		
Total	19	91188			

The appropriate distribution for the test statistic is $F_{3,16}$, and from Table 5 the critical value for $\alpha = 0.1$ is 2.46, so we would not reject the null hypothesis that there is no difference among the groups (the exact p-value is 0.12, as shown in the table above).

Chapter 12, Problem #24:

Concentrations of plasma epinephrine for ten dogs under three different types of anesthesia. To determine whether there is a treatment effect, we begin by looking at boxplots and descriptive statistics:

Variable Plasma	Treat 1 2 3	N 10 10 10	Mean 0.4340 0.4690 0.853	Median 0.3450 0.3900 0.855	StDev 0.2443 0.2053 0.448	
Variable Plasma	Treat 1 2 3		Minimum 0.1700 0.2100 0.280	Maximum 1.0000 0.8800 1.530	Q1 0.2875 0.3150 0.443	Q3 0.5550 0.6425 1 268

Descriptive statistics for plasma by anesthesia type:



It appears that there are differences among the three treatment groups. To determine whether the treatment effect is statistically significant, we produce a one-way ANOVA table:

Analysis	of Var	iance for	Plasma		
Source	DF	SS	MS	F	P
Treat	2	1.081	0.540	5.35	0.011
Error	27	2.725	0.101		
Total	29	3.806			

The distribution of the test statistic for anesthesia effect is $F_{2,27}$, and from Table 5 we can check that $F_{.975}(2,27) = 4.24 < 5.35$, so we can reject the null hypothesis at the 0.025 level (as shown in the table above, the exact *p*-value is 0.011). A normal probability plot of the residuals (below) indicates that the model provides a reasonably good fit to the data.



Note: If we wish to consider possible "dog" effects, a two-way ANOVA table gives the following results:

Analysis of Variance for Plasma

Source	DF	SS	MS	F	P
Dog	9	0.5169	0.0574	0.47	0.877
Treat	2	1.0808	0.5404	4.41	0.028
Error	18	2.2078	0.1227		
Total	29	3.8055			

While the "dog" effect is negligible, the treatment effect is no longer significant at the 0.025 level, which indicates some degree of interaction between the dogs and the treatment type in plasma levels. As the graph shown below illustrates, the treatment effect is not consistent across the group of 10 dogs.

Interaction Plot - Data Means for Plasma



Chapter 12, Problem #27:

Survival times for poisoned animals.

Part (a): Two-way ANOVA for survival times.

Table of mean survival times by poison type:

Poison	N	Time
I	16	6.1750
II	16	5.4313
III	16	2.7625

Table of mean survival times by treatment type:

Treatment	N	Time
A	12	3.1417
В	12	6.7667
С	12	3.9250
D	12	5.3250

Main Effects Plot - Data Means for Time







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Analysis of Variance for Time
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Source	DF	SS	MS	F	P
Poison	2	103.043	51.521	23.57	0.000
Treatment	3	91.904	30.635	14.01	0.000
Poison*Treatment	б	24.745	4.124	1.89	0.110
Error	36	78.692	2.186		
Total	47	298.385			

From the ANOVA table and the plots shown above, there appear to be significant effects due to both Poison type and Treatment. The interaction effect is marginally significant, although the null hypothesis of no interaction cannot be rejected at the 0.1 level.

Part (b): Two-way ANOVA for the reciprocals of the survival times

Table of mean reciprocal survival times by poison type:

Poison	Ν	1/Time
I	16	0.18007
II	16	0.22706
III	16	0.37971

Table of mean reciprocal survival times by treatment type:

N	1/Time
12	0.35193
12	0.18619
12	0.29472
12	0.21626
	N 12 12 12 12

Main Effects Plot - Data Means for 1/Time



Interaction Plot - Data Means for 1/Time



Analysis of Variance for 1/Time

Source	DF	SS	MS	F	P
Poison	2	0.348633	0.174316	72.84	0.000
Treatment	3	0.203962	0.067987	28.41	0.000
Poison*Treatment	б	0.015666	0.002611	1.09	0.386
Error	36	0.086151	0.002393		
Total	47	0.654412			

From the ANOVA table, both Poison and Treatment effects are highly significant for the reciprocal survival times, while the interaction effect is no longer significant.



To compare the results from (a) with the results from (b), we can look at plots of the residuals from each model:

A plot of the residuals against the fitted values for part (a) shows that the model provides a poor fit to longer survival times. The reciprocal transformation corrects for this problem, and thus the twoway ANOVA model provides a better fit for model (b).