Sassafras Manual

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1 Introduction

Sassafras is a shell mode program for data analysis.

Example

A die, which may be loaded, is tossed six times. The observed point values are one to six. Compute a 95% confidence interval for the true mean μ given the observed data.

```
data ;
input y ;
datalines ;
1
2
3
4
5
6
;
proc means clm ;
```

The following result is displayed.

```
                    Variable     95% CLM MIN     95% CLM MAX
                    Y                  1.537           5.463
```

Here is the same result using R.

```
> y = c(1,2,3,4,5,6)
> t.test(y)

One Sample t-test

data:  y
t = 4.5826, df = 5, p-value = 0.005934
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 1.536686 5.463314
```

2 Data Step

A data step is used to get data into the program.

> `data` *name* `;`
>
> `infile "`*filename*`" dlm="`*delims*`" firstobs=`*n* `;`
>
> `input` *list* `;`
>
> *var* `=` *expression* `;`
>
> `datalines ;` *data* `;`

Notes

1. *name* is optional.
2. The `dlm` and `firstobs` settings are optional.
3. *delims* is a sequence of delimiter characters. The default is tab, comma, and space.
4. *n* is the starting input record number. Use `firstobs=2` to skip a header in the data file.
5. *list* is a list of variable names separated by spaces. For each categorical variable place a `$` after the variable name.
6. Optional *var* = *expression* statements create new vectors in the data set.
7. The `datalines` statement is followed by observational data. At the end of the data a semicolon terminates the statement.

Example 1

The following example is a minimalist data step with in-line data.

```
data ;
input y ;
datalines ;
1
2
3
4
5
6
;
```

Example 2

Use @@ at the end of an input statement to allow multiple values on an input line.

```
data ;
input y @@ ;
datalines ;
1 2 3
4 5 6
;
```

Example 3

A dollar sign after an input variable indicates that the variable is categorical instead of numerical.

```
data ;
input trt$ y @@ ;
datalines ;
A 6    A 0    A 2    A 8   A 11
A 4    A 13   A 1    A 8   A 0
B 0    B 2    B 3    B 1   B 18
B 4    B 14   B 9    B 1   B 9
C 13   C 10   C 18   C 5   C 23
C 12   C 5    C 16   C 1   C 20
;
```

Example 4

An infile statement is used to read data from a file.

```
data ;
input color$ x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 y ;
infile "wine.txt" ;
```

Example 5

Expressions in a data step create new data vectors. The following example creates Y2 which is the input vector Y squared element-wise.

```
data ;
input color$ x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 y ;
infile "wine.txt" ;
y2 = y ** 2 ;
```

3 Anova Procedure

The anova procedure fits a classification model to data using ordinary least squares. The response variable must be numeric and the explanatory variables must be categorical.

> `proc anova data=`*name* `;`
>
> `model` *y* `=` *list* `;`
>
> `means` *list* `;`
>
> `means` *list* `/ lsd ttest alpha=`*value* `;`

Notes

1. `data=`*name* is optional. The default is data from the most recent data step.
2. *y* is the response variable which must be numeric.
3. *list* is one or more explanatory variables separated by spaces. The explanatory variables must be categorical. Interaction terms are specified using the syntax `A*B`.
4. The means statement can include one or more of the following options.

`lsd`	Compare treatment means using least significance difference
`ttest`	Compare treatment means using two sample t-test
`alpha`	Set the level of significance. Default is 0.05.

Example

```
data ;
input trt$ y @@ ;
datalines ;
A 6    A 0    A 2    A 8   A 11
A 4    A 13   A 1    A 8   A 0
B 0    B 2    B 3    B 1   B 18
B 4    B 14   B 9    B 1   B 9
C 13   C 10   C 18   C 5   C 23
C 12   C 5    C 16   C 1   C 20
;

proc anova ;
model y = trt ;
means trt / lsd ttest ;
```

The following result is displayed.

```
                              Analysis of Variance

    Source      DF      Sum of Squares        Mean Square      F Value      Pr > F
    Model        2        293.60000000       146.80000000         3.98      0.0305
    Error       27        995.10000000        36.85555556
    Total       29       1288.70000000
```

R-Square	Coeff Var	Root MSE	Y Mean
0.227826	76.846553	6.070878	7.900000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
TRT	2	293.60000000	146.80000000	3.98	0.0305

Mean Response

TRT	N	Mean Y	95% CI MIN	95% CI MAX
A	10	5.300000	1.360938	9.239062
B	10	6.100000	2.160938	10.039062
C	10	12.300000	8.360938	16.239062

Least Significant Difference Test

TRT	TRT	Delta Y	95% CI MIN	95% CI MAX	t Value	Pr > |t|
A	B	-0.800000	-6.370676	4.770676	-0.29	0.7705
A	C	-7.000000	-12.570676	-1.429324	-2.58	0.0157 *
B	A	0.800000	-4.770676	6.370676	0.29	0.7705
B	C	-6.200000	-11.770676	-0.629324	-2.28	0.0305 *
C	A	7.000000	1.429324	12.570676	2.58	0.0157 *
C	B	6.200000	0.629324	11.770676	2.28	0.0305 *

Two Sample t-Test

TRT	TRT	Delta Y	95% CI MIN	95% CI MAX	t Value	Pr > |t|
A	B	-0.800000	-5.922306	4.322306	-0.33	0.7466
A	C	-7.000000	-12.664270	-1.335730	-2.60	0.0182 *
B	A	0.800000	-4.322306	5.922306	0.33	0.7466
B	C	-6.200000	-12.467653	0.067653	-2.08	0.0523
C	A	7.000000	1.335730	12.664270	2.60	0.0182 *
C	B	6.200000	-0.067653	12.467653	2.08	0.0523

Mean response table

The confidence interval for a treatment mean is computed as follows.

$$\bar{y}_i \pm t(1-\alpha/2, dfe) \cdot \sqrt{\frac{MSE}{n_i}}$$

Recall that MSE is an estimate of model variance. From the anova table

```
Error       27        995.10000000        36.85555556
```

we obtain

$$MSE = 36.85555556$$
$$dfe = 27$$

Using R, the confidence interval for the mean of treatment A can be checked as follows.

```
> MSE = 36.8556
> dfe = 27
> t = qt(0.975,dfe)
> 5.3 - t * sqrt(MSE/10)
[1] 1.360934
> 5.3 + t * sqrt(MSE/10)
[1] 9.239066
```

Least significant difference test

The least significant difference of two means $\bar{y}_i$ and $\bar{y}_j$ is

$$LSD_{ij} = t(1 - \alpha/2, dfe) \cdot \sqrt{MSE \cdot \left(\frac{1}{n_i} + \frac{1}{n_j}\right)}$$

The corresponding confidence interval is

$$\bar{y}_i - \bar{y}_j \pm LSD_{ij}$$

Two sample t-test

The two sample t-test is computed as follows.

$$\begin{aligned}
SSE &= \widehat{Var}_i \cdot (n_i - 1) + \widehat{Var}_j \cdot (n_j - 1) \\
dfe &= n_i + n_j - 2 \\
MSE &= \frac{SSE}{dfe} \\
SE &= \sqrt{MSE \cdot \left(\frac{1}{n_i} + \frac{1}{n_j}\right)} \\
t^* &= \frac{\bar{y}_i - \bar{y}_j}{SE}
\end{aligned}$$

SSE is the sum of squares error recovered from variance estimates, dfe is the degrees of freedom error, MSE is mean square error, SE is the standard error, and t^* is the test statistic. The confidence interval is

$$\bar{y}_i - \bar{y}_j \pm t(1 - \alpha/2, dfe) \cdot SE$$

The null hypothesis is that the two treatment means are equal.

$$H_0 : \bar{y}_i = \bar{y}_j$$

If $|t^*|$ is greater than the critical value $t(1 - \alpha/2, dfe)$, or equivalently, if the confidence interval does not cross zero, then reject H_0 and conclude that the treatment means are not equal. The following R session uses the above equations to duplicate the Sassafras result for treatments A and B.

```
> YA = c(6,0,2,8,11,4,13,1,8,0)
> YB = c(0,2,3,1,18,4,14,9,1,9)
> sse = var(YA) * (length(YA) - 1) + var(YB) * (length(YB) - 1)
> dfe = length(YA) + length(YB) - 2
> mse = sse / dfe
> se = sqrt(mse * (1 / length(YA) + 1 / length(YB)))
> t = (mean(YA) - mean(YB)) / se
> mean(YA) - mean(YB) - qt(0.975,dfe) * se
[1] -5.922307
> mean(YA) - mean(YB) + qt(0.975,dfe) * se
[1] 4.322307
> 2 * (1 - pt(abs(t),dfe))
[1] 0.746606
```

The same result is obtained with the t-test function.

```
> t.test(YA,YB,var.equal=TRUE)

Two Sample t-test

data:  YA and YB
t = -0.3281, df = 18, p-value = 0.7466
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -5.922307  4.322307
sample estimates:
mean of x mean of y
      5.3       6.1
```

4 Means Procedure

The means procedure prints statistics about a data set.

proc means data=*name* alpha=*value* maxdec=*n* *stats* ;

var *list* ;

class *list* ;

Notes

1. The settings that follow the `means` keyword are optional. The settings can appear in any order.

2. If `data` is not specified then the default is data from the most recent data step.

3. `alpha` sets the level of significance. The default is 0.05.

4. `maxdec` sets the decimal precision in the output. n ranges from 0 to 8. The default is 3.

5. *stats* is a list of statistics keywords from the following table.

`clm`	Confidence limits of the mean
`max`	Maximum value
`mean`	Mean value
`min`	Minimum value
`n`	Number of observations
`range`	max − min
`std`	Standard deviation s
`stddev`	Another keyword for s
`stderr`	Standard error $s/\sqrt{n}$
`var`	Variance s^2

   If *stats* is not specified then the default list is `n mean std min max`.

6. The optional `var` statement specifies which variables to print. The default is all variables. Variable names in *list* are separated by spaces.

7. The optional `class` statement prints statistics for each level of the categorical variables in *list*. Variable names in *list* are separated by spaces.

Example 1

The following example reads in the wine[1] data set and shows the default action of proc means.

[1]P. Cortez, A. Cerdeira, F. Almeida, T. Matos and J. Reis. *Modeling wine preferences by data mining from physicochemical properties.* In Decision Support Systems, Elsevier, 47(4):547-553, 2009.

```
data wine ;
input color$ x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 y ;
infile "wine.txt" ;

proc means ;
```

The following result is displayed.

```
Variable        N        Mean     Std Dev     Minimum     Maximum
X1           6497       7.215       1.296       3.800      15.900
X2           6497       0.340       0.165       0.080       1.580
X3           6497       0.319       0.145       0.000       1.660
X4           6497       5.443       4.758       0.600      65.800
X5           6497       0.056       0.035       0.009       0.611
X6           6497      30.525      17.749       1.000     289.000
X7           6497     115.745      56.522       6.000     440.000
X8           6497       0.995       0.003       0.987       1.039
X9           6497       3.219       0.161       2.720       4.010
X10          6497       0.531       0.149       0.220       2.000
X11          6497      10.492       1.193       8.000      14.900
Y            6497       5.818       0.873       3.000       9.000
```

Example 2

The following example adds a var statement to show Y by itself. Also, the desired statistics are specified.

```
data wine ;
input color$ x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 y ;
infile "wine.txt" ;

proc means n mean clm ;
var y ;
```

The following result is displayed.

```
Variable        N      Mean     95% CLM MIN     95% CLM MAX
Y            6497     5.818           5.797           5.840
```

Example 3

The following example adds a class statement to show statistics for each wine color.

```
data wine ;
input color$ x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 y ;
infile "wine.txt" ;

proc means n mean clm ;
var y ;
class color ;
```

The following result is displayed.

```
COLOR     Variable        N      Mean     95% CLM MIN     95% CLM MAX
red       Y            1599     5.636           5.596           5.676
white     Y            4898     5.878           5.853           5.903
```

5 Print Procedure

The print procedure prints data in a data set.

> `proc print data=`*name* `;`
>
> `var` *list* `;`

Notes

1. `data=`*name* is optional. The default is data from the most recent data step.
2. The optional `var` statement specifies which variables to print. The default is all variables. Variable names in *list* are separated by spaces.

Example

The following example reads a data set and prints it.

```
data ;
input trt$ y @@ ;
datalines ;
A 6    A 0    A 2    A 8   A 11
A 4    A 13   A 1    A 8   A 0
B 0    B 2    B 3    B 1   B 18
B 4    B 14   B 9    B 1   B 9
;

proc print ;
```

The following result is displayed.

```
Obs     TRT      Y
  1     A        6
  2     A        0
  3     A        2
  4     A        8
  5     A       11
  6     A        4
  7     A       13
  8     A        1
  9     A        8
 10     A        0
 11     B        0
 12     B        2
 13     B        3
 14     B        1
 15     B       18
 16     B        4
 17     B       14
 18     B        9
 19     B        1
 20     B        9
```

6 Reg Procedure

The reg procedure fits a linear model to data using ordinary least squares. The response variable must be numeric. For models with no intercept, anova results will differ from R. This is because R switches to uncorrected sums of squares for models with no intercept.

> `proc reg data=`*name* `;`
>
> `model` *y* `=` *list* `;`
>
> `model` *y* `=` *list* `/ noint ;`

Notes

1. `data=`*name* is optional. The default is data from the most recent data step.
2. *y* is the response variable which must be numeric.
3. *list* is a list of explanatory variables separated by spaces. If functions of explanatory variables are required then they must be defined in the data step.
4. The `noint` option fits a linear model with no intercept term.

Example 1

The following example reads in the wine data set and fits a linear model with no intercept term.

```
data ;
input color$ x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 y ;
infile "wine.txt" ;

proc reg ;
model y = color x1 / noint ;
```

The following result is displayed.

```
                              Analysis of Variance

              DF     Sum of Squares     Mean Square     F Value     Pr > F
    Model      2           72.79210        36.39605       48.42     0.0000
    Error   6494         4880.89360         0.75160
    Total   6496         4953.68570

              Root MSE              0.86695     R-Square     0.0147
              Dependent Mean        5.81838     Adj R-Sq     0.0144
              Coeff Var            14.90018

                              Parameter Estimates

                         Estimate      Std Err      t Value      Pr > |t|
         COLOR red        5.77309      0.08194        70.45        0.0000
         COLOR white      5.99084      0.06628        90.39        0.0000
         X1              -0.01647      0.00950        -1.73        0.0829
```

Example 2

The following exercise is from *Econometrics*[2]. Using data from a 1963 paper by Marc Nerlove, estimate parameters for the model

$$\log(\text{COST}) = \beta_0 + \beta_1 \log(\text{KWH}) + \beta_2 \log(\text{PL}) + \beta_3 \log(\text{PF}) + \beta_4 \log(\text{PK}) + \varepsilon$$

where COST is production cost, KWH is kilowatt hours, PL is price of labor, PF is price of fuel, and PK is price of capital.

```
data ;
infile "nerlove.txt" ;
input COST KWH PL PF PK ;
LCOST = log(COST) ;
LKWH = log(KWH) ;
LPL = log(PL) ;
LPF = log(PF) ;
LPK = log(PK) ;

proc reg ;
model LCOST = LKWH LPL LPF LPK ;
```

The following result is displayed.

```
                              Analysis of Variance

              DF     Sum of Squares     Mean Square     F Value     Pr > F
    Model      4          269.51482        67.37870      437.69     0.0000
    Error    140           21.55201         0.15394
    Total    144          291.06683

             Root MSE              0.39236     R-Square     0.9260
             Dependent Mean        1.72466     Adj R-Sq     0.9238
             Coeff Var            22.74969

                              Parameter Estimates

                      Estimate      Std Err       t Value      Pr > |t|
          Intercept   -3.52650      1.77437         -1.99        0.0488
          LKWH         0.72039      0.01747         41.24        0.0000
          LPL          0.43634      0.29105          1.50        0.1361
          LPF          0.42652      0.10037          4.25        0.0000
          LPK         -0.21989      0.33943         -0.65        0.5182
```

The following code can be pasted into R to obtain a similar result.

```
d = read.table("nerlove.txt")
lcost = log(d[,1])
lkwh = log(d[,2])
lpl = log(d[,3])
lpf = log(d[,4])
lpk = log(d[,5])
m = lm(lcost ~ lkwh + lpl + lpf + lpk)
summary(m)
```

[2] Hansen, Bruce E. *Econometrics.* www.ssc.wisc.edu/~bhansen

The following result is displayed in R.

```
Call:
lm(formula = lcost ~ lkwh + lpl + lpf + lpk)

Residuals:
     Min       1Q   Median       3Q      Max
-0.97784 -0.23817 -0.01372  0.16031  1.81751

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.52650    1.77437  -1.987   0.0488 *
lkwh         0.72039    0.01747  41.244  < 2e-16 ***
lpl          0.43634    0.29105   1.499   0.1361
lpf          0.42652    0.10037   4.249 3.89e-05 ***
lpk         -0.21989    0.33943  -0.648   0.5182
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3924 on 140 degrees of freedom
Multiple R-squared:  0.926,Adjusted R-squared:  0.9238
F-statistic: 437.7 on 4 and 140 DF,  p-value: < 2.2e-16
```

Example 3

The following model uses the “trees” data set from R.

```
data ;
input Girth Height Volume ;
LG = log(Girth) ;
LH = log(Height) ;
LV = log(Volume) ;
datalines ;
  8.3     70   10.3
  8.6     65   10.3
  8.8     63   10.2
 10.5     72   16.4
 10.7     81   18.8
 10.8     83   19.7
 11.0     66   15.6
 11.0     75   18.2
 11.1     80   22.6
 11.2     75   19.9
 11.3     79   24.2
 11.4     76   21.0
 11.4     76   21.4
 11.7     69   21.3
 12.0     75   19.1
 12.9     74   22.2
 12.9     85   33.8
 13.3     86   27.4
 13.7     71   25.7
 13.8     64   24.9
```

```
 14.0     78   34.5
 14.2     80   31.7
 14.5     74   36.3
 16.0     72   38.3
 16.3     77   42.6
 17.3     81   55.4
 17.5     82   55.7
 17.9     80   58.3
 18.0     80   51.5
 18.0     80   51.0
 20.6     87   77.0
;

proc reg ;
model LV = LG LH ;
```

The following result is displayed.

```
                               Analysis of Variance

    Source      DF      Sum of Squares      Mean Square      F Value      Pr > F
    Model        2          1.53213547       0.76606773       613.19      0.0000
    Error       28          0.03498056       0.00124931
    Total       30          1.56711603

                Root MSE             0.03535      R-Square      0.9777
                Dependent Mean       1.42133      Adj R-Sq      0.9761
                Coeff Var            2.48679

                               Parameter Estimates

         Parameter        Estimate       Std Err       t Value       Pr > |t|
         (Intercept)      -2.88007       0.34734         -8.29         0.0000
         log(Girth)        1.98265       0.07501         26.43         0.0000
         log(Height)       1.11712       0.20444          5.46         0.0000
```

Let us see if the above parameters correspond to the volume of a cone given by

$$V = \frac{\pi}{12} d^2 h$$

where d is the diameter (girth) and h is the height of the cone. The model from the regression is

$$\log V = -2.88 + 1.98 \log d + 1.12 \log h$$

Take the antilog of both sides and obtain

$$V = 0.00132 \times d^{1.98} \times h^{1.12}$$

The exponents resemble the volume formula but the overall coefficient 0.00132 is two orders of magnitude smaller than $\pi/12 \approx 0.262$. It turns out the discrepancy is due to the units of measure. Girth is measured in inches while height and volume are measured in feet. To convert girth from inches to feet requires a factor of 1/12. Hence the leading coefficient should be

$$\frac{\pi}{12} \times \frac{1}{144} \approx 0.00182$$

which is in the ballpark of 0.00132 from the regression model.

Let us compare the Reg results to R. The following block of code can be pasted directly into the R shell prompt.

```
d=log10(trees[,1])
h=log10(trees[,2])
V=log10(trees[,3])
m=lm(V~d+h)
summary(m)
```

This is the R result, which matches Reg.

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.88007    0.34734  -8.292 5.06e-09 ***
d            1.98265    0.07501  26.432  < 2e-16 ***
h            1.11712    0.20444   5.464 7.81e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03535 on 28 degrees of freedom
Multiple R-squared:  0.9777,Adjusted R-squared:  0.9761
F-statistic: 613.2 on 2 and 28 DF,  p-value: < 2.2e-16
```

7 Review

Analysis of Variance

The components of an analysis of variance table are computed as follows.

	DF	SS	Mean Square	F-value	p-value
Model	$p-1$	SSR	$MSR = SSR/(p-1)$	$F^* = MSR/MSE$	$1 - F(F^*, p-1, n-p)$
Error	$n-p$	SSE	$MSE = SSE/(n-p)$		
Total	$n-1$	SST			

In the table, n is the number of observations and p is the number of model parameters including the intercept term if there is one. The sums of squares are computed as follows.

$$SSR = \sum(\hat{y}_i - \bar{y})^2$$
$$SSE = \sum(y_i - \hat{y}_i)^2$$
$$SST = \sum(y_i - \bar{y})^2$$

Recall that MSE is an estimate of model variance.

$$MSE = \hat{\sigma}^2$$

A simple way to model the response variable is to use the average $\bar{y}$. The p-value above indicates whether or not the regression model is better than $\bar{y}$. The null hypothesis is that the regression model is no better than the average, that is

$$H_0 : SST = SSE$$

The test for H_0 is known as an omnibus test because an equivalent hypothesis is

$$H_0 : \beta_1 = \beta_2 = \cdots = \beta_{p-1} = 0$$

Under H_0 we have $SSR = 0$ hence another equivalent hypothesis is

$$H_0 : F^* = 0$$

The test statistic F^* is used because it has a well-known distribution. Recall that the p-value is (loosely) the probability that H_0 is true. Hence for small p-values, reject H_0 and conclude that the regression model is better than $\bar{y}$.

Confidence interval of the mean

The confidence interval of the mean is

$$\bar{x} \pm t_{1-\alpha/2,n-1} \frac{s}{\sqrt{n}}$$

where $\bar{x}$ is the observed mean, s is the observed standard deviation, n is the number of observations, and $t_{1-\alpha/2,n-1}$ is the quantile function. In R, the confidence interval of the mean of `1:10` can be computed as follows.

```
> x = 1:10
> n = length(x)
> alpha = 0.05
> mean(x) - qt(1-alpha/2,n-1) * sd(x)/sqrt(n)
[1] 3.334149
> mean(x) + qt(1-alpha/2,n-1) * sd(x)/sqrt(n)
[1] 7.665851
```

Alternatively, the `t.test` function can be used.

```
> t.test(1:10)

One Sample t-test

data:  1:10
t = 5.7446, df = 9, p-value = 0.0002782
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 3.334149 7.665851
sample estimates:
mean of x
      5.5
```

Recall that the quantile function is the inverse of the cumulative distribution function. Let F be the cumulative distribution function. Then

$$F(t_{1-\alpha/2,n-1}) = 1 - \alpha/2$$

For example, in R we have

```
> t = qt(0.975,8)
> t
[1] 2.306004
> pt(t,8)
[1] 0.975
```

8 Anova results

Consider the following anova program and its output. Note that the least significant difference test has more power (more stars) than the t-test.

```
data ;
input trt$ y @@ ;
datalines ;
A 6    A 0    A 2    A 8   A 11
A 4    A 13   A 1    A 8   A 0
B 0    B 2    B 3    B 1   B 18
B 4    B 14   B 9    B 1   B 9
C 13   C 10   C 18   C 5   C 23
C 12   C 5    C 16   C 1   C 20
;

proc anova ;
model y = trt ;
means trt / lsd ttest ;
```

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	293.60000000	146.80000000	3.98	0.0305
Error	27	995.10000000	36.85555556		
Total	29	1288.70000000			

R-Square	Coeff Var	Root MSE	Y Mean
0.227826	76.846553	6.070878	7.900000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
TRT	2	293.60000000	146.80000000	3.98	0.0305

Mean Response

TRT	N	Mean Y	95% CI MIN	95% CI MAX
A	10	5.300000	1.360937	9.239063
B	10	6.100000	2.160937	10.039063
C	10	12.300000	8.360937	16.239063

Least Significant Difference Test

TRT	TRT	Delta Y	95% CI MIN	95% CI MAX	t Value	Pr > |t|	
A	B	-0.800000	-6.370677	4.770677	-0.29	0.7705	
A	C	-7.000000	-12.570677	-1.429323	-2.58	0.0157	*
B	A	0.800000	-4.770677	6.370677	0.29	0.7705	
B	C	-6.200000	-11.770677	-0.629323	-2.28	0.0305	*
C	A	7.000000	1.429323	12.570677	2.58	0.0157	*
C	B	6.200000	0.629323	11.770677	2.28	0.0305	*

Two Sample t-Test

TRT	TRT	Delta Y	95% CI MIN	95% CI MAX	t Value	Pr > |t|
A	B	-0.800000	-5.922307	4.322307	-0.33	0.7466

A	C	-7.000000	-12.664270	-1.335730	-2.60	0.0182 *
B	A	0.800000	-4.322307	5.922307	0.33	0.7466
B	C	-6.200000	-12.467653	0.067653	-2.08	0.0523
C	A	7.000000	1.335730	12.664270	2.60	0.0182 *
C	B	6.200000	-0.067653	12.467653	2.08	0.0523

Let us take a closer look at the analysis of variance table.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	293.60000000	146.80000000	3.98	0.0305
Error	27	995.10000000	36.85555556		
Total	29	1288.70000000			

This is how the table values are computed where n is the number of observations and p is the number of model parameters.

Source	DF	Sum of Squares	Mean Square	F-value	p-value
Model	$p-1$	SSR	MSR = SSR/$(p-1)$	F^* = MSR/MSE	$1-F(F^*, p-1, n-p)$
Error	$n-p$	SSE	MSE = SSE/$(n-p)$		
Total	$n-1$	SST			

For the following sum of squares calculations, y are observed values and $\hat{y}$ are predicted values.

$$
\begin{aligned}
\text{SSR} &= \sum(\hat{y}_i - \bar{y})^2 = \text{SST} - \text{SSE} \\
\text{SSE} &= \sum(y_i - \hat{y}_i)^2 \\
\text{SST} &= \sum(y_i - \bar{y})^2
\end{aligned}
$$

The p-value in the anova table is used for checking that the regression model is better than the mean $\bar{y}$. The null hypothesis is that the model is no better than the mean, that is

$$H_0 : \text{SSE} = \text{SST}$$

Under H_0 we have SSR $= 0$ hence MSR $= 0$ and

$$H_0 : F^* = 0$$

Recall that the p-value is (loosely) the probability that H_0 is true. Hence for small p-values, reject H_0 and conclude that the regression model is better than the mean.
Let us take a closer look at the mean response table.

Mean Response

TRT	N	Mean Y	95% CI MIN	95% CI MAX
A	10	5.300000	1.360937	9.239063
B	10	6.100000	2.160937	10.039063
C	10	12.300000	8.360937	16.239063

Recall that the confidence interval for a treatment mean is

$$\bar{y} \pm t(1-\alpha/2, \text{dfe}) \times \text{SE}, \quad \text{SE} = \sqrt{\frac{\text{MSE}}{n}}$$

where SE is standard error and MSE (mean square error) is estimated model variance. From the analysis of variance table at the top of the output we have

Source	DF	Sum of Squares	Mean Square
Error	27	995.10000000	36.85555556

Hence

$$\text{dfe} = 27, \quad \text{MSE} = 36.85555556$$

The confidence interval for the mean of treatment A can be checked by typing the following into R.

```
ybar = 5.3
n = 10
MSE = 36.85555556
dfe = 27
alpha = 0.05
SE = sqrt(MSE / n)
t = qt(1 - alpha/2, dfe) * SE
ybar - t
ybar + t
```

R prints the following results.

```
[1] 1.360937
[1] 9.239063
```

The R results match the mean response table for treatment A.

TRT	N	Mean Y	95% CI MIN	95% CI MAX
A	10	5.300000	1.360937	9.239063

Let us take a closer look at the least significant difference table.

Least Significant Difference Test

TRT	TRT	Delta Y	95% CI MIN	95% CI MAX	t Value	Pr > |t|
A	B	-0.800000	-6.370677	4.770677	-0.29	0.7705

The least significant difference of two treatment means $\bar{y}_A$ and $\bar{y}_B$ is

$$\text{LSD} = t(1-\alpha/2, \text{dfe}) \times \text{SE}, \quad \text{SE} = \sqrt{\text{MSE} \times \left(\frac{1}{n_A} + \frac{1}{n_B}\right)}$$

The corresponding confidence interval is

$$(\bar{y}_A - \bar{y}_B) \pm \text{LSD}$$

The confidence interval in the LSD table can be checked by typing the following into R.

```
ybarA = 5.3
ybarB = 6.1
nA = 10
nB = 10
MSE = 36.85555556
dfe = 27
alpha = 0.05
SE = sqrt(MSE * (1/nA + 1/nB))
LSD = qt(1 - alpha/2, dfe) * SE
ybarA - ybarB - LSD
ybarA - ybarB + LSD
```

R prints the following results.

```
[1] -6.370677
[1] 4.770677
```

The R results match the confidence interval in the LSD table.

TRT	TRT	Delta Y	95% CI MIN	95% CI MAX	t Value	Pr > |t|
A	B	-0.800000	-6.370677	4.770677	-0.29	0.7705

Let us take a closer look at the t-test table.

Two Sample t-Test

TRT	TRT	Delta Y	95% CI MIN	95% CI MAX	t Value	Pr > |t|
A	B	-0.800000	-5.922307	4.322307	-0.33	0.7466

The t-test confidence interval is

$$(\bar{y}_A - \bar{y}_B) \pm t(1-\alpha/2, \mathrm{dfe}) \times \mathrm{SE}$$

where

$$\mathrm{SE} = \sqrt{\frac{\mathrm{SSE}}{\mathrm{dfe}} \times \left(\frac{1}{n_A} + \frac{1}{n_B}\right)}, \quad \mathrm{SSE} = \sum (y_A - \bar{y}_A)^2 + \sum (y_B - \bar{y}_B)^2$$

and

$$\mathrm{dfe} = n_A + n_B - 2$$

The confidence interval can be checked by typing the following into R.

```
yA = c(6,0,2,8,11,4,13,1,8,0)
yB = c(0,2,3,1,18,4,14,9,1,9)
nA = length(yA)
nB = length(yB)
dfe = nA + nB - 2
SSE = var(yA) * (nA - 1) + var(yB) * (nB - 1)
MSE = SSE / dfe
SE = sqrt(MSE * (1/nA + 1/nB))
alpha = 0.05
t = qt(1 - alpha/2, dfe) * SE
mean(yA) - mean(yB) - t
mean(yA) - mean(yB) + t
```

R prints the following result which matches the above t-test table.

```
[1] -5.922307
[1] 4.322307
```

R's t-test function gives the same result.

```
t.test(yA,yB,var.equal=TRUE)

Two Sample t-test

data:  yA and yB
t = -0.32812, df = 18, p-value = 0.7466
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -5.922307  4.322307
```