

**Flicker data:** Measures of ‘critical flicker frequency’ for 19 subjects with different eye colors. An individual’s “critical flicker frequency is the highest frequency at which the flicker in a flickering light source can be detected. At frequencies above critical frequency, light source appears to be continuous”

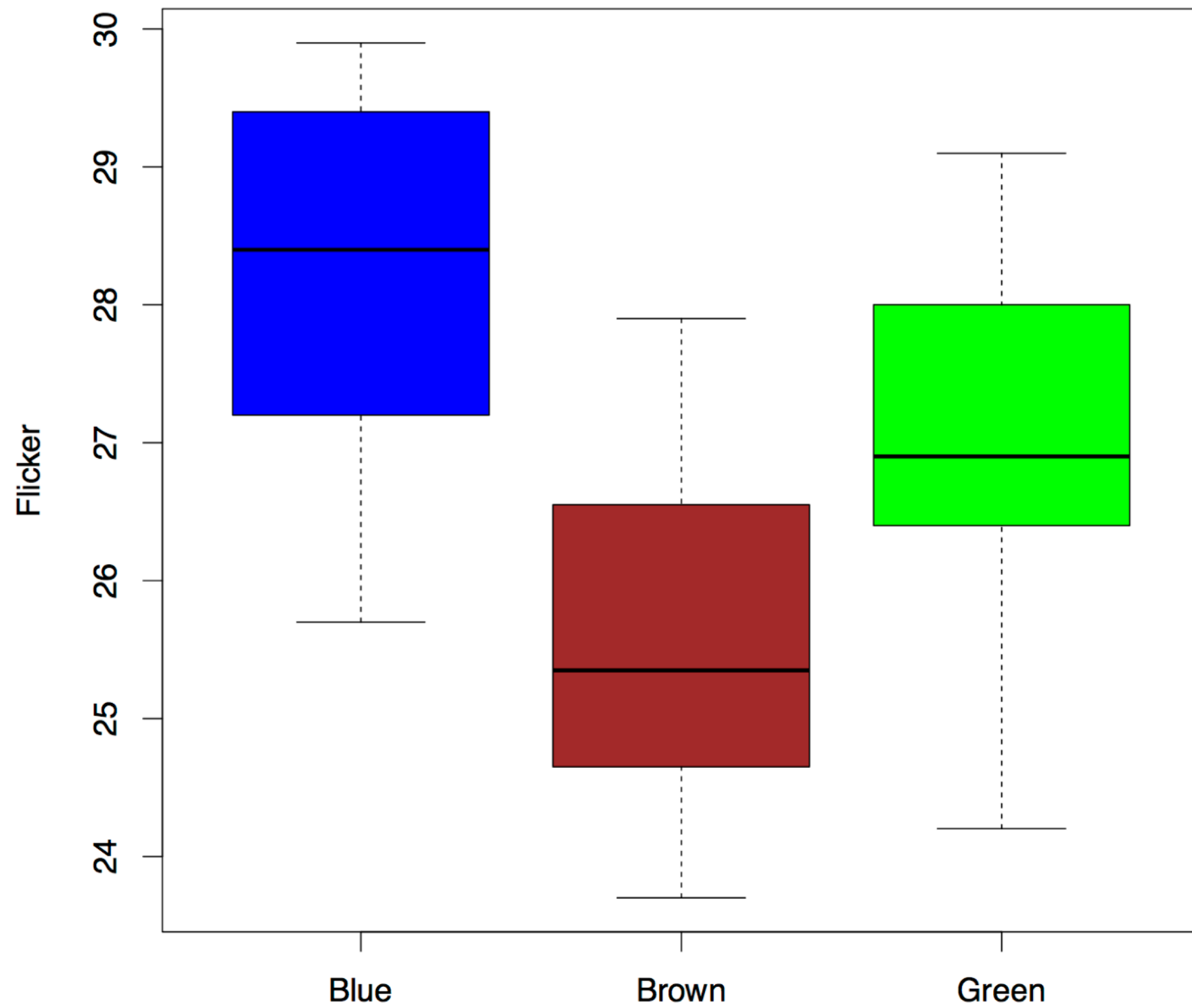
(a)		
Brown	Green	Blue
26.8	26.4	25.7
27.9	24.2	27.2
23.7	28.0	29.9
25.0	26.9	28.5
26.3	29.1	29.4
24.8		28.3
25.7		
24.5		

(b)	
Colour	Flicker
Brown	26.8
Brown	27.9
Brown	23.7
Brown	25.0
Brown	26.3
Brown	24.8
Brown	25.7
Brown	24.5
Green	26.4
Green	24.2
Green	28.0
Green	26.9
Green	29.1
Blue	25.7
Blue	27.2
Blue	29.9
Blue	28.5
Blue	29.4
Blue	28.3

```
> flicker = read.table(file=
+"http://www.statsci.org/data/general/flicker.txt",
+ header=TRUE, stringsAsFactors=TRUE)
> is.factor(flicker$Colour)
[1] TRUE
> levels(flicker$Colour)
[1] "Blue"    "Brown"    "Green"
> unclass(flicker$Colour)
 [1] 2 2 2 2 2 2 2 2 2 3 3 3 3 3 1 1 1 1 1 1
attr(,"levels")
[1] "Blue"    "Brown"    "Green"

> attach(flicker)
> colors_flicker=c('Blue','Brown','Green')
> boxplot(Flicker ~ Colour, ylab="Flicker",
col=colors_flicker)
```

# ANOVA



```
> meansd = function(x) c(mean=mean(x), sd=sd(x))
```

```
> by(Flicker, Colour, FUN=meansd)
```

```
Colour: Blue
```

mean	sd
28.166667	1.527962

---

```
Colour: Brown
```

mean	sd
25.587500	1.365323

---

```
Colour: Green
```

mean	sd
26.920000	1.843095

**we can also use `var.equal=TRUE`  
in such case `p-value=.02325`**



```
> oneway.test(Flicker ~ Colour)
```

One-way analysis of means (not assuming equal variances)

```
data: Flicker and Colour
```

```
F = 5.0505, num df = 2.0000, denom df = 8.9259, p-value = 0.03412
```

```
> L = lm(Flicker ~ Colour)
> summary(L)
```

```
Call:
lm(formula = Flicker ~ Colour)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.7200	-0.8771	0.1125	1.1462	2.3125

**ColourBlue**

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	28.1667	0.6317	44.588	< 2e-16
ColourBrown	-2.5792	0.8357	-3.086	0.00708
ColourGreen	-1.2467	0.9370	-1.331	0.20200

Residual standard error: 1.547 on 16 degrees of freedom  
Multiple R-squared: 0.3751, Adjusted R-squared: 0.297  
F-statistic: 4.802 on 2 and 16 DF, p-value: 0.02325

```
> model.matrix(L)
      (Intercept) ColourBrown ColourGreen
1              1           1           0
2              1           1           0
3              1           1           0
4              1           1           0
5              1           1           0
6              1           1           0
7              1           1           0
8              1           1           0
9              1           0           1
10             1           0           1
11             1           0           1
12             1           0           1
13             1           0           1
14             1           0           0
15             1           0           0
16             1           0           0
17             1           0           0
18             1           0           0
19             1           0           0
```

```
> M = aov(Flicker ~ Colour)
> model.tables(M, type="means")
```

Tables of means

Grand mean

26.75263

Colour

	Blue	Brown	Green
--	------	-------	-------

	28.17	25.59	26.92
--	-------	-------	-------

rep	6.00	8.00	5.00
-----	------	------	------

```
> model.tables(M)
```

Tables of effects

Colour

	Blue	Brown	Green
--	------	-------	-------

	1.414	-1.165	0.1674
--	-------	--------	--------

rep	6.000	8.000	5.0000
-----	-------	-------	--------

```
> anova(L)
```

```
Analysis of Variance Table
```

```
Response: Flicker
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Colour	2	22.997	11.4986	4.8023	0.02325
Residuals	16	38.310	2.3944		

- Residual mean square error is equal to the square residual standard error of the linear model, i.e.,  $(1.547)^2 = 2.39$



```
> L1=lm(Flicker ~ Colour - 1)
> summary(L1)
```

Call:

```
lm(formula = Flicker ~ Colour - 1)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.7200	-0.8771	0.1125	1.1462	2.3125

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
ColourBlue	28.1667	0.6317	44.59	<2e-16
ColourBrown	25.5875	0.5471	46.77	<2e-16
ColourGreen	26.9200	0.6920	38.90	<2e-16

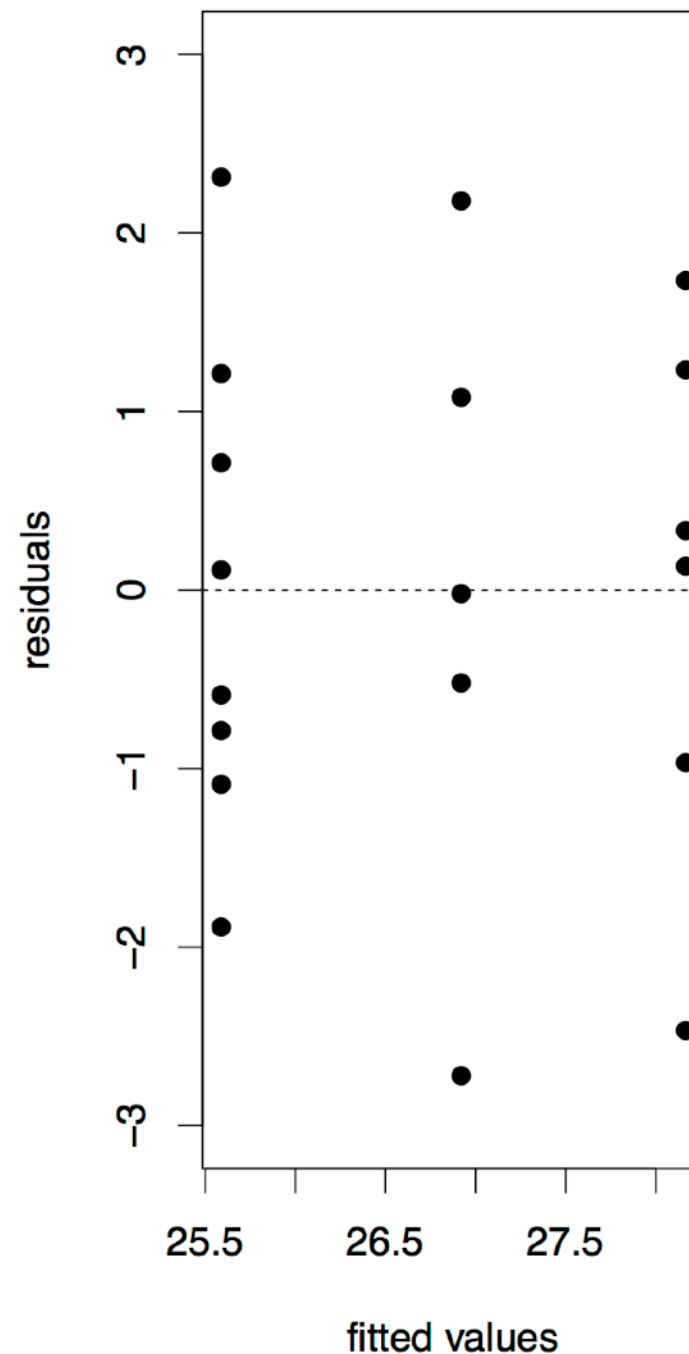
Residual standard error: 1.547 on 16 degrees of freedom  
Multiple R-squared: 0.9972, Adjusted R-squared: 0.9967  
F-statistic: 1896 on 3 and 16 DF, p-value: < 2.2e-16

**Careful with the interpretation of the F test and R<sup>2</sup> in this case!**

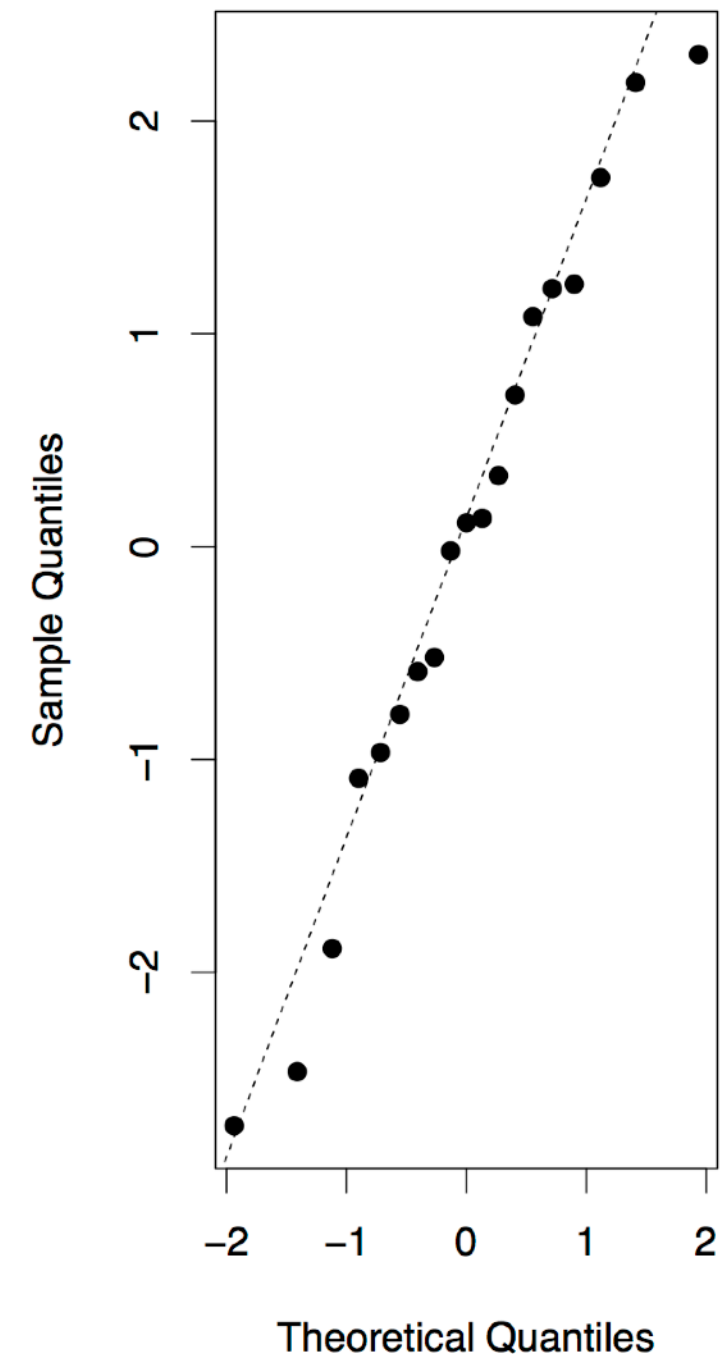
# ANOVA

```
> plot(L$fit, L$res, pch=19, xlab="fitted values", ylab="residuals",  
+       main="Residuals vs Fitted Values", ylim=c(-3, 3))  
> abline(h=0, lty=2)  
> qqnorm(L$res, pch=19)  
> qqline(L$res, lty=2)
```

**Residuals vs Fitted Values**



**Normal Q-Q Plot**



## Comparison of treatment means

- Fisher's least significant difference:

$$H_0 : \mu_i = \mu_j \quad vs \quad H_1 : \mu_i \neq \mu_j, \quad 1 \leq i < j \leq a$$

$$T = \frac{\bar{y}_i - \bar{y}_j}{\sqrt{MSE \left( \frac{1}{n_i} + \frac{1}{n_j} \right)}}$$

Under the null hypothesis this is distributed according to a Student-t distribution with  $N - a$  with  $N = \sum_{i=1}^a n_i$

Then, the least significant difference is defined as:

$$LSD = t_{N-a}^{\alpha/2} \sqrt{MSE \left( \frac{1}{n_i} + \frac{1}{n_j} \right)}$$

Then, the pair of means for groups  $i$  and  $j$  are significantly different if  $|\bar{y}_i - \bar{y}_j| > LSD$

```
> MSE = 2.3944
> t97.5 = qt(.975, df=16) #97.5th percentile of t
> n = table(Colour) #sample sizes
> means = by(Flicker, Colour, mean) #treatment means
> outer(means, means, "-")
```

```
      Colour
Colour      Blue      Brown      Green
Blue      0.000000  2.579167  1.246667
Brown    -2.579167  0.000000 -1.332500
Green    -1.246667  1.332500  0.000000
```

```
> n
Colour
Blue Brown Green
   6    8    5
```

```
> t97.5 * sqrt(MSE * outer(1/n, 1/n, "+"))
```

Colour

Colour	Blue	Brown	Green
Blue	1.893888	1.771570	1.986326
Brown	1.771570	1.640155	1.870064
Green	1.986326	1.870064	2.074650

Then,

Pair	diff	LSD
Blue-Brown	2.5792	1.7716
Blue-Green	1.2467	1.9863
Brown-Green	-1.3325	1.8701



**Problem:** Multiple testing. You may reject the null when it is true. Use this only after F-test

- The function `pairwise.t.test` summarizes pairwise t-test with p-values adjusted to control for the type 1 error rate:

```
> pairwise.t.test(Flicker, Colour)
```

```
Pairwise comparisons using t tests with pooled SD
```

```
data: Flicker and Colour
```

```
      Blue  Brown
Brown 0.021  -
Green 0.301 0.301
```

```
P value adjustment method: holm
```

- You can customize the p-value adjustment method using `p.adjust`, available options: `holm`, `hochberg`, `hommel`, `bonferroni`, `BH`, `BY`, `fdr`, or `none`

```
> pairwise.t.test(Flicker, Colour, p.adjust="none")
```

Pairwise comparisons using t tests with pooled SD

data: Flicker and Colour

	Blue	Brown
Brown	0.0071	–
Green	0.2020	0.1504

P value adjustment method: none

```
> pairwise.t.test(Flicker, Colour, p.adjust="bonferroni")
```

Pairwise comparisons using t tests with pooled SD

data: Flicker and Colour


	Blue	Brown
Brown	0.021	–
Green	0.606	0.451

P value adjustment method: bonferroni

- Tuckey's multiple comparisons method: based on the range. The studentized range statistic is given by:

$$q = \frac{\bar{y}_{max} - \bar{y}_{min}}{\sqrt{\frac{MSE}{n}}}$$

We need to compute **Quantile of the studentized-range distribution**


$$w = q_{\alpha}(a, df) \sqrt{\frac{MSE}{n}}$$

with  $a$  the number of treatments,  $n$  the group sample size and  $df$  the degrees of freedom for the error. Then,

$$|\bar{y}_i - \bar{y}_j| > w$$

For unequal group sizes use the Tukey-Kramer method with



$$w = q_{\alpha}(a, df) \sqrt{\frac{MSE}{2} \left( \frac{1}{n_i} + \frac{1}{n_j} \right)}$$

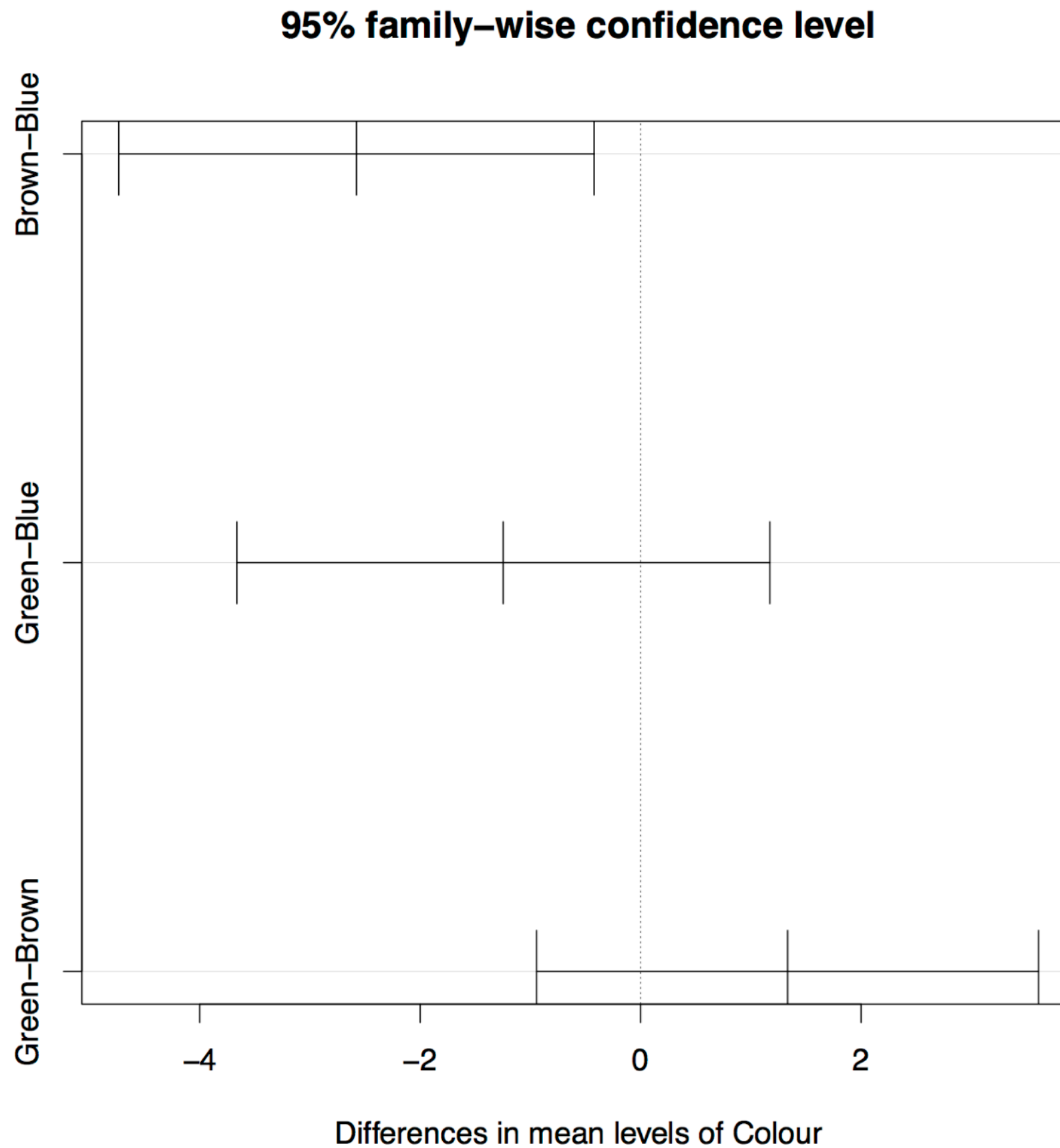
Tukey's multiple comparison procedure is sometimes called "Tukey's Honest Significant Difference" (TukeyHSD)

```
> qtukey(.95, nmeans=3, df=16)
[1] 3.649139
> M=aov(L)
> TukeyHSD(M)
  Tukey multiple comparisons of means
    95% family-wise confidence level
```

```
Fit: aov(formula = Flicker ~ Colour)
```

```
$Colour
```

		diff	lwr	upr	p adj
Brown-Blue	-2.579167	-4.7354973	-0.422836	0.0183579	
Green-Blue	-1.246667	-3.6643959	1.171063	0.3994319	
Green-Brown	1.332500	-0.9437168	3.608717	0.3124225	



# Randomized block model

**Randomized block designs:** We want to model the effect of a treatment or factor when the samples are not independent.

Example, Exam Scores: Exam scores in five subjects for 88 students. A one-way ANOVA is not appropriate: exam scores for each subject are not independent given that the same 88 students took each exam. We want to incorporate the effect of the student in the model in order to appropriately study the factor (exam topics).

```
> library(bootstrap)
> head(scor)
  mec  vec  alg  ana  sta
1   77   82   67   67   81
2   63   78   80   70   81
3   75   73   71   66   81
4   55   72   63   70   68
5   63   63   65   70   63
6   53   61   72   64   73
```

**Mechanics:** Closed book

**Vectors:** Closed book

**Algebra:** Open book

**Analysis:** Open book

**Statistics:** Open book

# Randomized block model


```
> sapply(scor, mean, data=scor)
      mec      vec      alg      ana      sta
38.95455 50.59091 50.60227 46.68182 42.30682
> scor.long = stack(scor)
> block = factor(rep(1:88, times=5))
> scor.long = data.frame(scor.long, block)
> head(scor.long) #top
  values ind block
1      77 mec     1
2      63 mec     2
3      75 mec     3
4      55 mec     4
5      63 mec     5
6      53 mec     6
> tail(scor.long) #bottom
  values ind block
435     18 sta    83
436     17 sta    84
437     18 sta    85
438     21 sta    86
439     20 sta    87
440     14 sta    88
```

# Randomized block model


```
> names(scor.long) = c("score", "exam", "student")
> str(scor.long)
'data.frame':440 obs. of 3 variables:
 $ score   : num  77 63 75 55 63 53 51 59 62 64 ...
 $ exam    : Factor w/ 5 levels "alg","ana","mec",...: 3 3 3 3 3 3 3
3 3 3 ...
 $ student: Factor w/ 88 levels "1","2","3","4",...: 1 2 3 4 5 6 7
8 9 10 ...
```

**Model:**

type of exam



$$y_{i,j} = \mu + \alpha_i + \beta_j + \epsilon_{i,j}$$



student effect

# Randomized block model

```
> L = aov(score ~ exam + student, data=scor.long)
```

```
> summary(L)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
exam	4	9315	2328.7	21.201	1.16e-15 ***
student	87	58313	670.3	6.102	< 2e-16 ***
Residuals	348	38225	109.8		

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

```
> model.tables(L, cterms="exam")
```

Tables of effects

exam

exam

alg	ana	mec	sta	vec
4.775	0.855	-6.873	-3.520	4.764

```
> model.tables(L, cterms="exam", type="mean")
```

Tables of means

Grand mean

45.82727

exam

exam

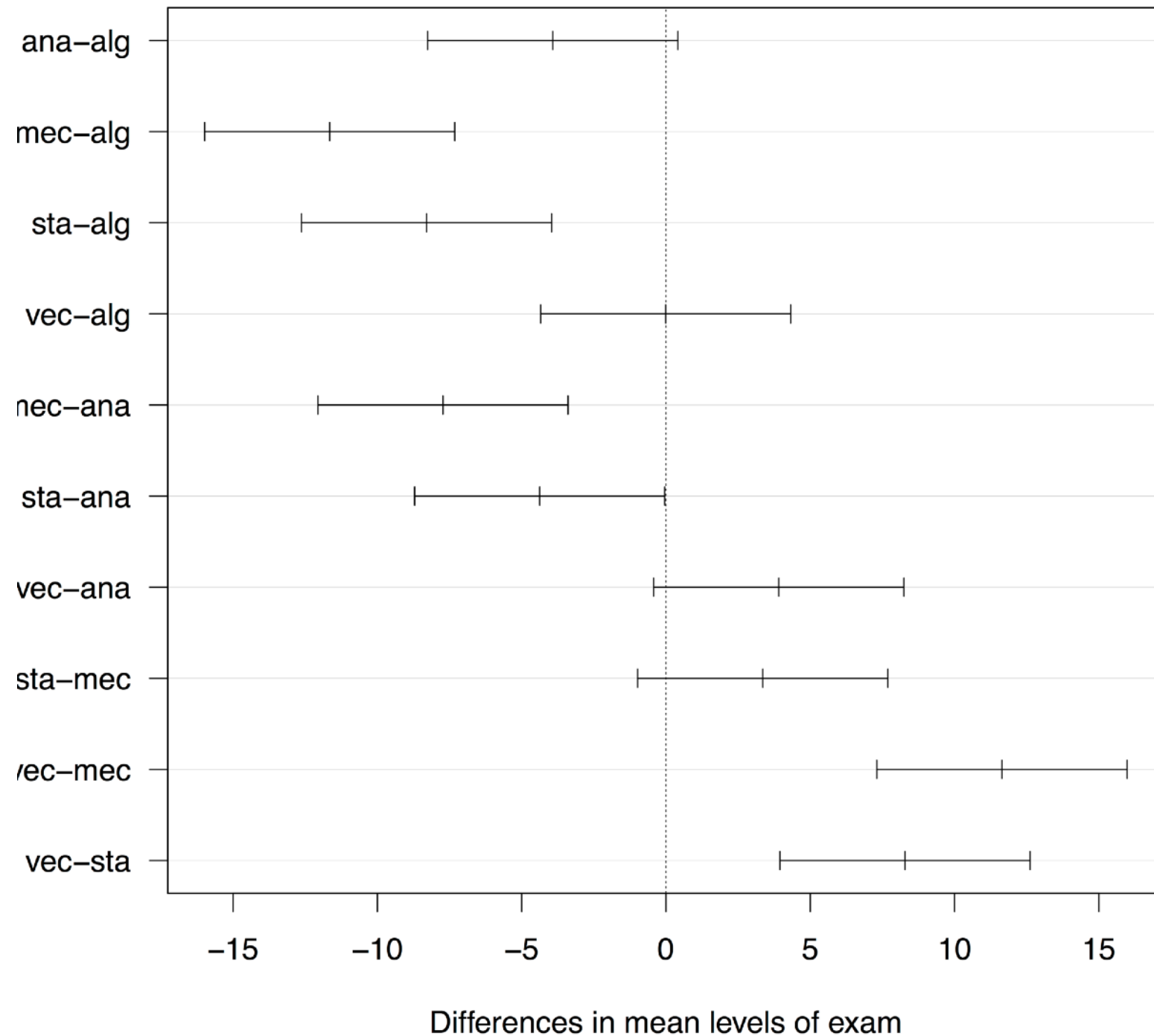
alg	ana	mec	sta	vec
50.60	46.68	38.95	42.31	50.59

# Randomized block model

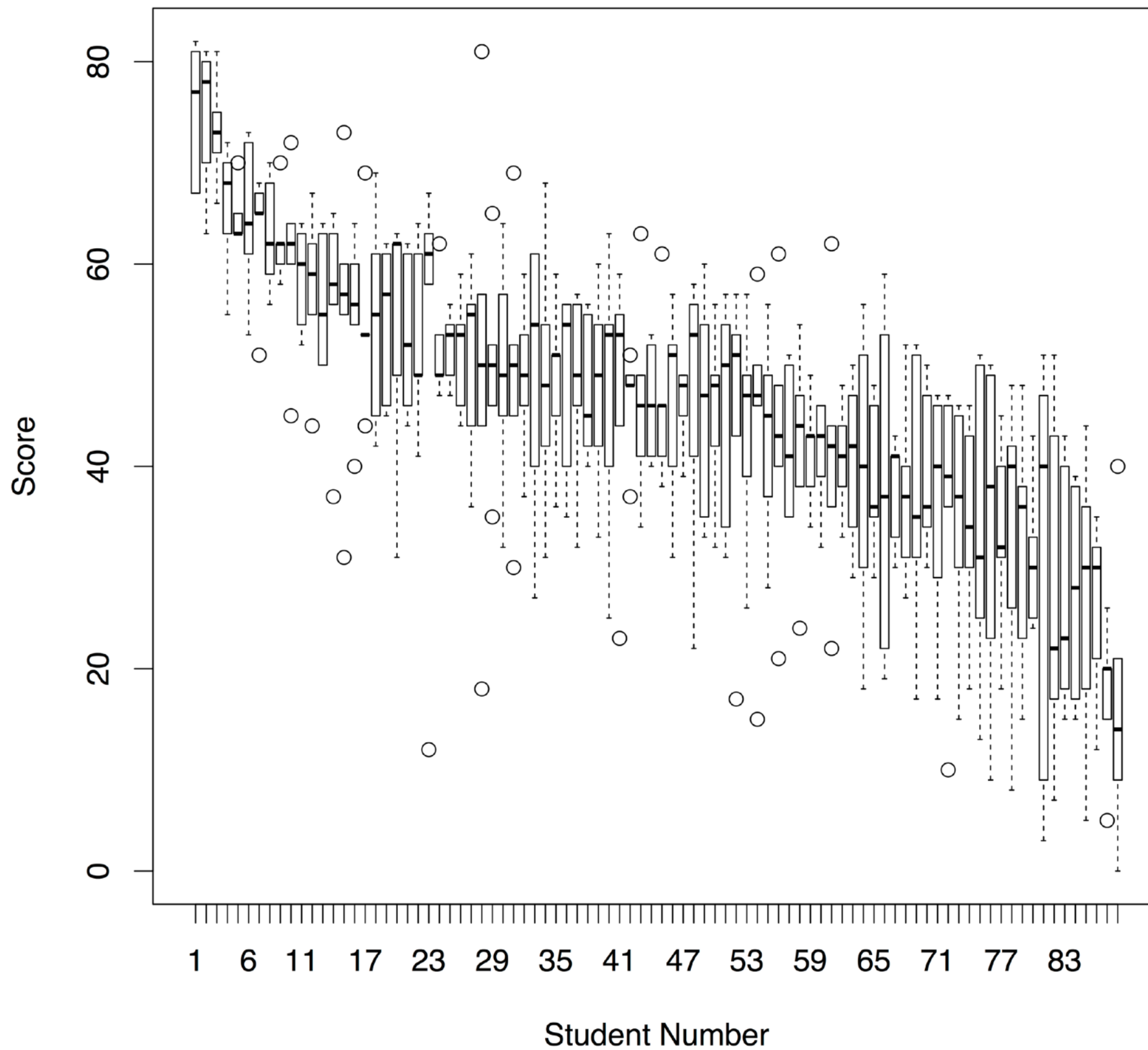
```
> CIs = TukeyHSD(L, which=1)
```

```
> plot(CIs, las=1)
```

**95% family-wise confidence level**



# Randomized block model





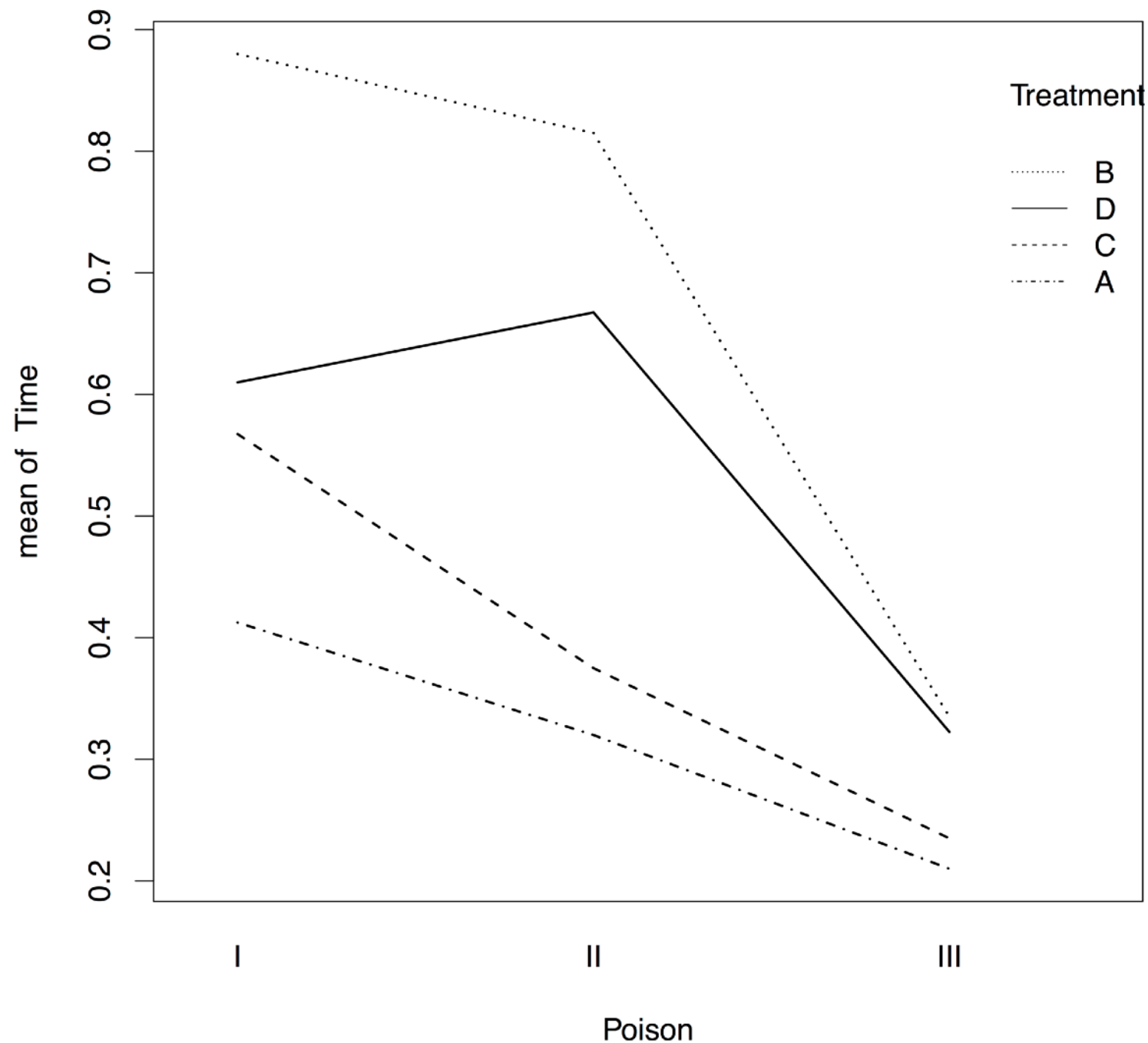
# Two-way ANOVA

Example: Survival times in units of 10 hours for animals exposed to 3 types of poison and 4 types of antidotes

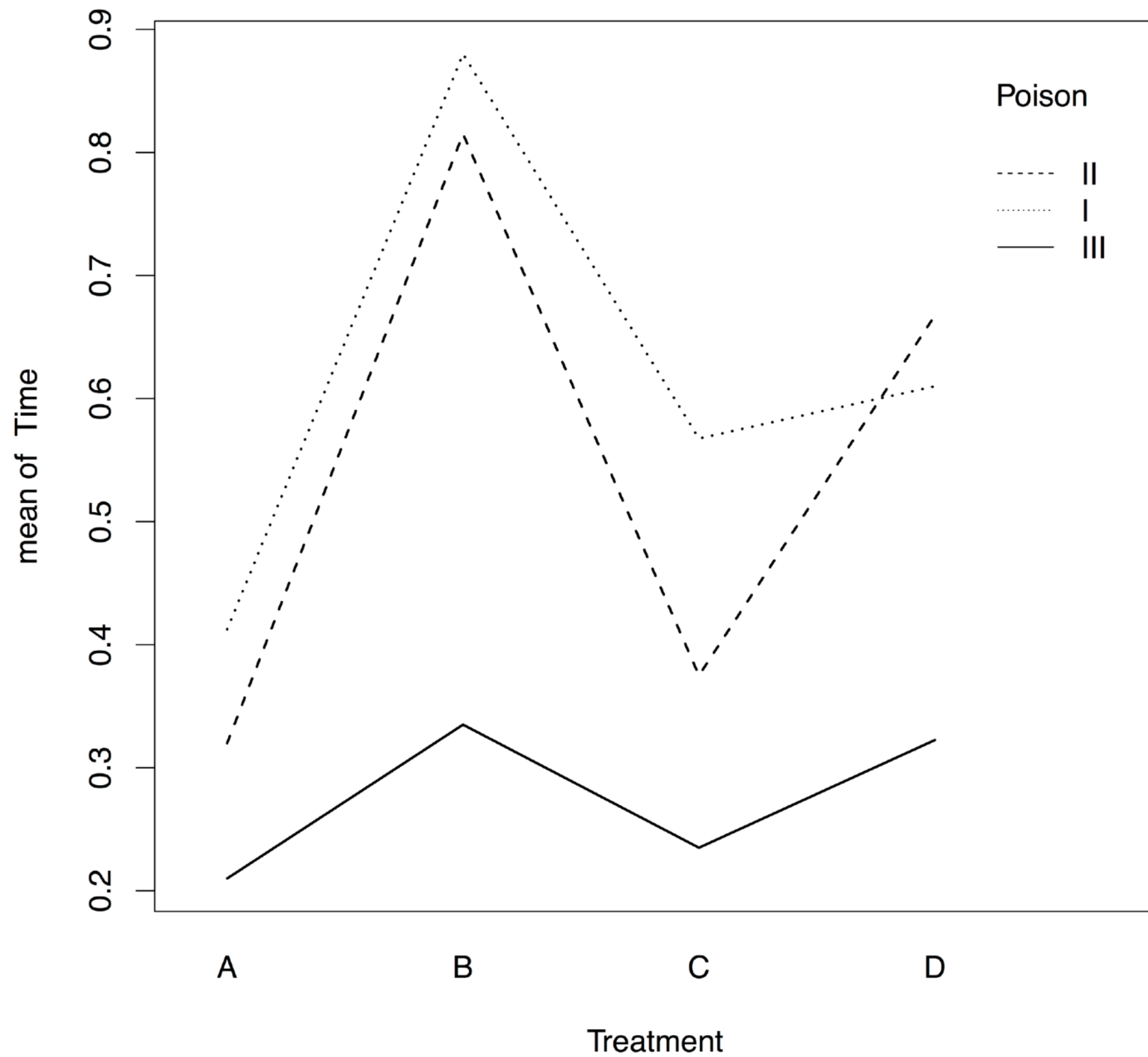
poison	treatment			
	A	B	C	D
I	0.31	0.82	0.43	0.45
	0.45	1.10	0.45	0.71
	0.46	0.88	0.63	0.66
	0.43	0.72	0.76	0.62
II	0.36	0.92	0.44	0.56
	0.20	0.61	0.35	1.02
	0.40	0.49	0.31	0.71
	0.23	1.24	0.40	0.38
III	0.22	0.30	0.23	0.30
	0.21	0.37	0.25	0.36
	0.18	0.38	0.24	0.31
	0.23	0.29	0.22	0.33

## Interaction plots

```
> with(data=poison, expr={  
+   interaction.plot(Poison, Treatment, response=Time,lwd=2)  
+   interaction.plot(Treatment, Poison, response=Time,lwd=2),  
+   })
```



# Two-way ANOVA



# Two-way ANOVA

```
> L = aov(Time ~ Poison * Treatment, data = poison)
> anova(L)
```

Analysis of Variance Table

Response: Time

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Poison	2	1.03708	0.51854	23.3314	3.176e-07
Treatment	3	0.92012	0.30671	13.8000	3.792e-06
Poison:Treatment	6	0.25027	0.04171	1.8768	0.1118
Residuals	36	0.80010	0.02222		

- We see that the interaction effect is not significant

# Two-way ANOVA

```
> L1 = aov(Time ~ Poison + Treatment, data = poison)
> anova(L1)
```

Analysis of Variance Table

Response: Time

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Poison	2	1.03708	0.51854	20.734	5.448e-07
Treatment	3	0.92012	0.30671	12.264	6.743e-06
Residuals	42	1.05037	0.02501		

- The Poison and Treatment effects are significant

# Two-way ANOVA

```
> model.tables(L, type="means")
```

```
Tables of means
```

```
Grand mean
```

```
0.4791667
```

```
Poison
```

```
Poison
```

```
      I      II      III
```

```
0.6175 0.5444 0.2756
```

```
Treatment
```

```
Treatment
```

```
      A      B      C      D
```

```
0.3142 0.6767 0.3925 0.5333
```

```
Poison:Treatment
```

```
      Treatment
```

```
Poison A      B      C      D
```

```
  I    0.4125 0.8800 0.5675 0.6100
```

```
 II    0.3200 0.8150 0.3750 0.6675
```

```
 III   0.2100 0.3350 0.2350 0.3225
```

# Two-way ANOVA

```
> model_L=lm(Time~Poison*Treatment, data=poison)
```

```
> summary(model_L)
```

Call:

```
lm(formula = Time ~ Poison * Treatment, data = poison)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.32500	-0.04875	0.00625	0.04312	0.42500

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	0.41250	0.07454	5.534	2.92e-06
PoisonII	-0.09250	0.10542	-0.877	0.3860
PoisonIII	-0.20250	0.10542	-1.921	0.0627
TreatmentB	0.46750	0.10542	4.435	8.32e-05
TreatmentC	0.15500	0.10542	1.470	0.1501
TreatmentD	0.19750	0.10542	1.874	0.0691
PoisonII:TreatmentB	0.02750	0.14908	0.184	0.8547
PoisonIII:TreatmentB	-0.34250	0.14908	-2.297	0.0275
PoisonII:TreatmentC	-0.10000	0.14908	-0.671	0.5066
PoisonIII:TreatmentC	-0.13000	0.14908	-0.872	0.3890
PoisonII:TreatmentD	0.15000	0.14908	1.006	0.3211
PoisonIII:TreatmentD	-0.08500	0.14908	-0.570	0.5721

# Two-way ANOVA

```
> model_L1=lm(Time~Poison+Treatment, data=poison)
> summary(model_L1)
Call:
lm(formula = Time ~ Poison + Treatment, data = poison)
Residuals:
```

Min	1Q	Median	3Q	Max
-0.25188	-0.09646	-0.01469	0.06203	0.49812

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	0.45250	0.05591	8.093	4.15e-10
PoisonII	-0.07312	0.05591	-1.308	0.19803
PoisonIII	-0.34187	0.05591	-6.115	2.72e-07
TreatmentB	0.36250	0.06456	5.615	1.42e-06
TreatmentC	0.07833	0.06456	1.213	0.23179
TreatmentD	0.21917	0.06456	3.395	0.00151

Residual standard error: 0.1581 on 42 degrees of freedom  
Multiple R-squared: 0.6508, Adjusted R-squared: 0.6092  
F-statistic: 15.65 on 5 and 42 DF, p-value: 1.094e-08



# Two-way ANOVA

```
> TukeyHSD(L1, which=c("Poison", "Treatment"))
```

```
Tukey multiple comparisons of means
```

```
95% family-wise confidence level
```

```
Fit: aov(formula = Time ~ Poison + Treatment, data = poison)
```

```
$Poison
```

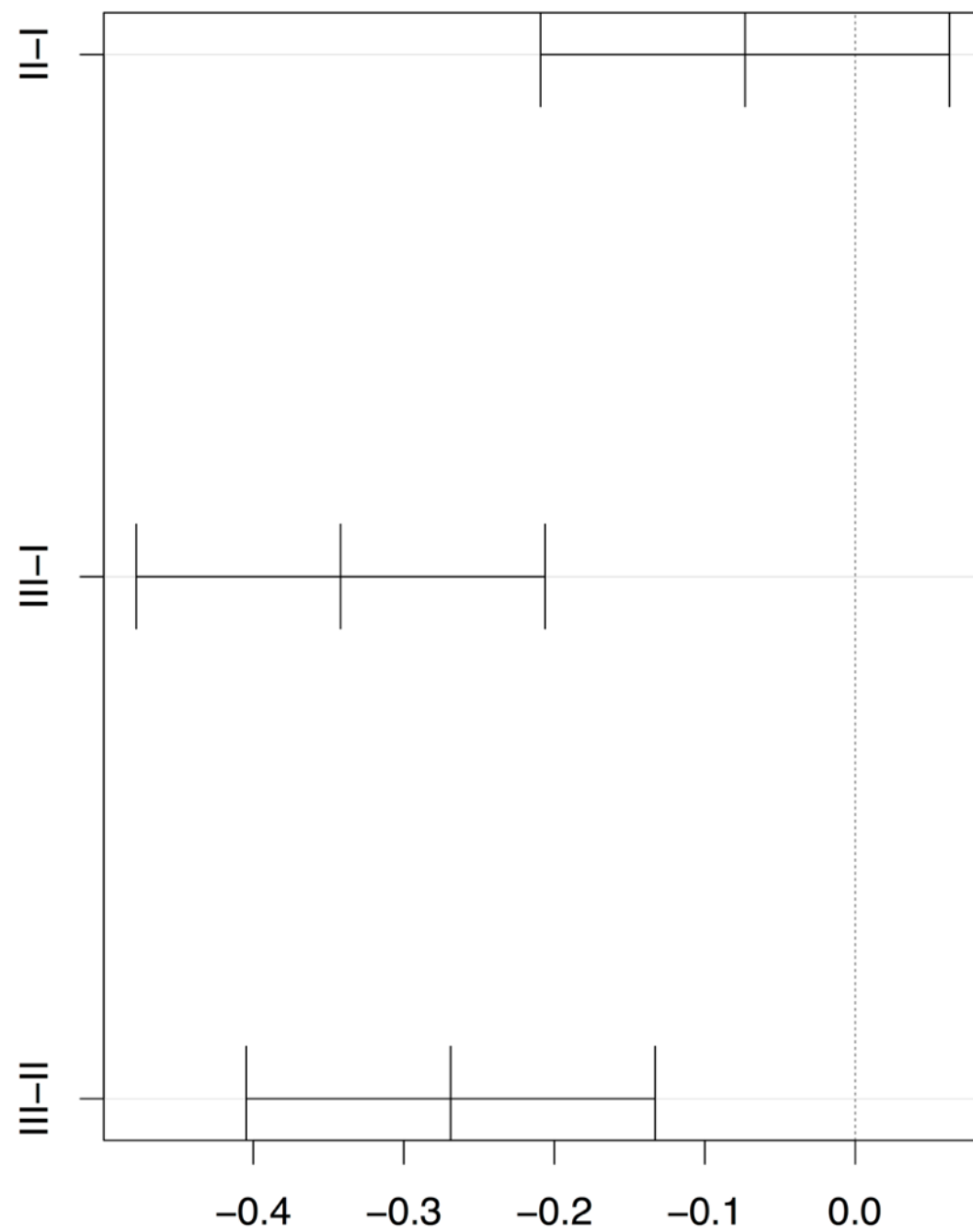
		diff	lwr	upr	p adj
II-I	-0.073125	-0.2089618	0.06271181	0.3987984	
III-I	-0.341875	-0.4777118	-0.20603819	<u>0.00000008</u>	
III-II	-0.268750	-0.4045868	-0.13291319	<u>0.00000582</u>	

```
$Treatment
```

		diff	lwr	upr	p adj
B-A	0.36250000	0.18980177	0.5351982	<u>0.00000083</u>	
C-A	0.07833333	-0.09436490	0.2510316	0.6219967	
D-A	0.21916667	0.04646843	0.3918649	<u>0.0079262</u>	
C-B	-0.28416667	-0.45686490	-0.1114684	<u>0.0004077</u>	
D-B	-0.14333333	-0.31603157	0.0293649	0.1344032	
D-C	0.14083333	-0.03186490	0.3135316	0.1451135	

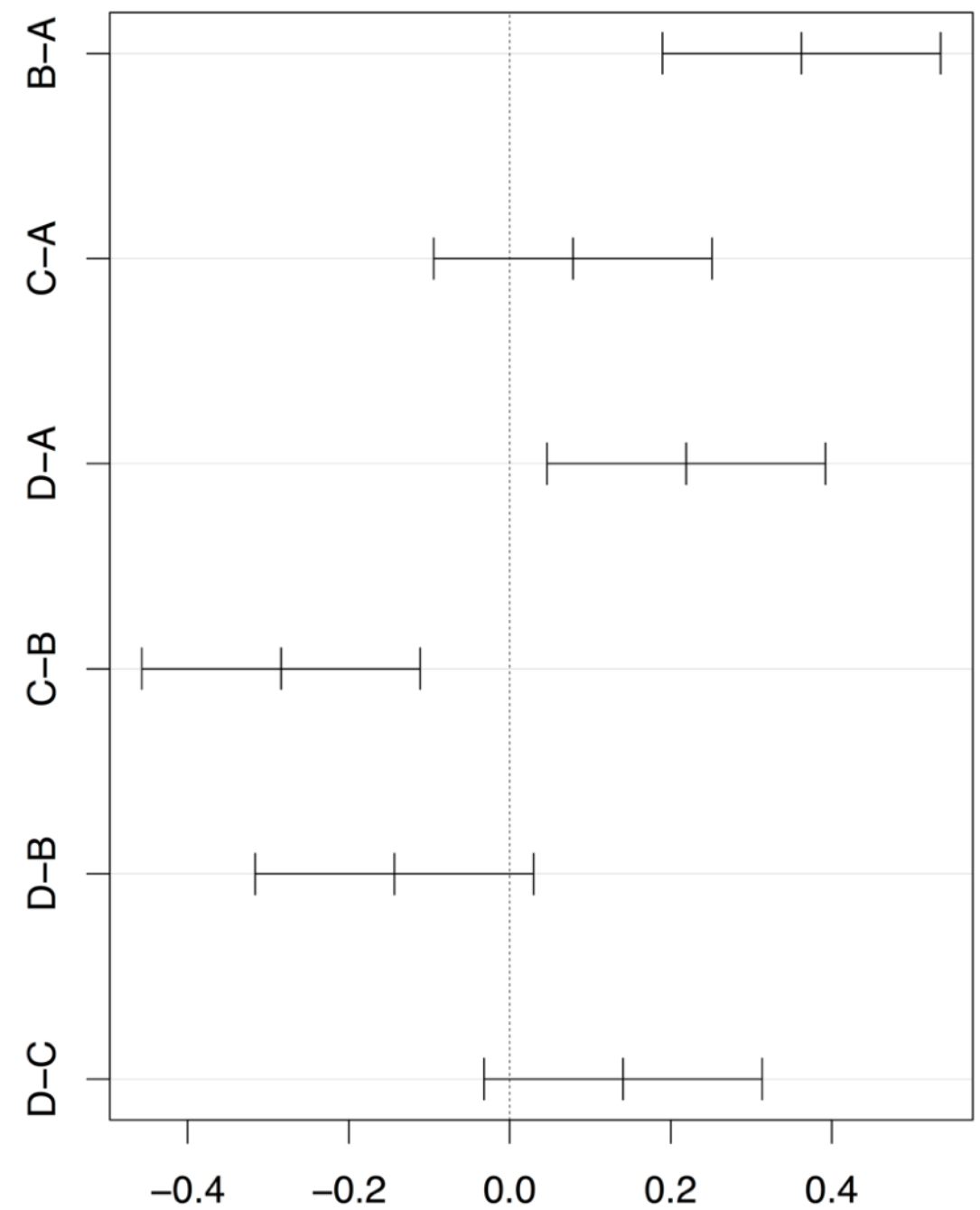
# Two-way ANOVA

95% family-wise confidence level



Differences in mean levels of Poison

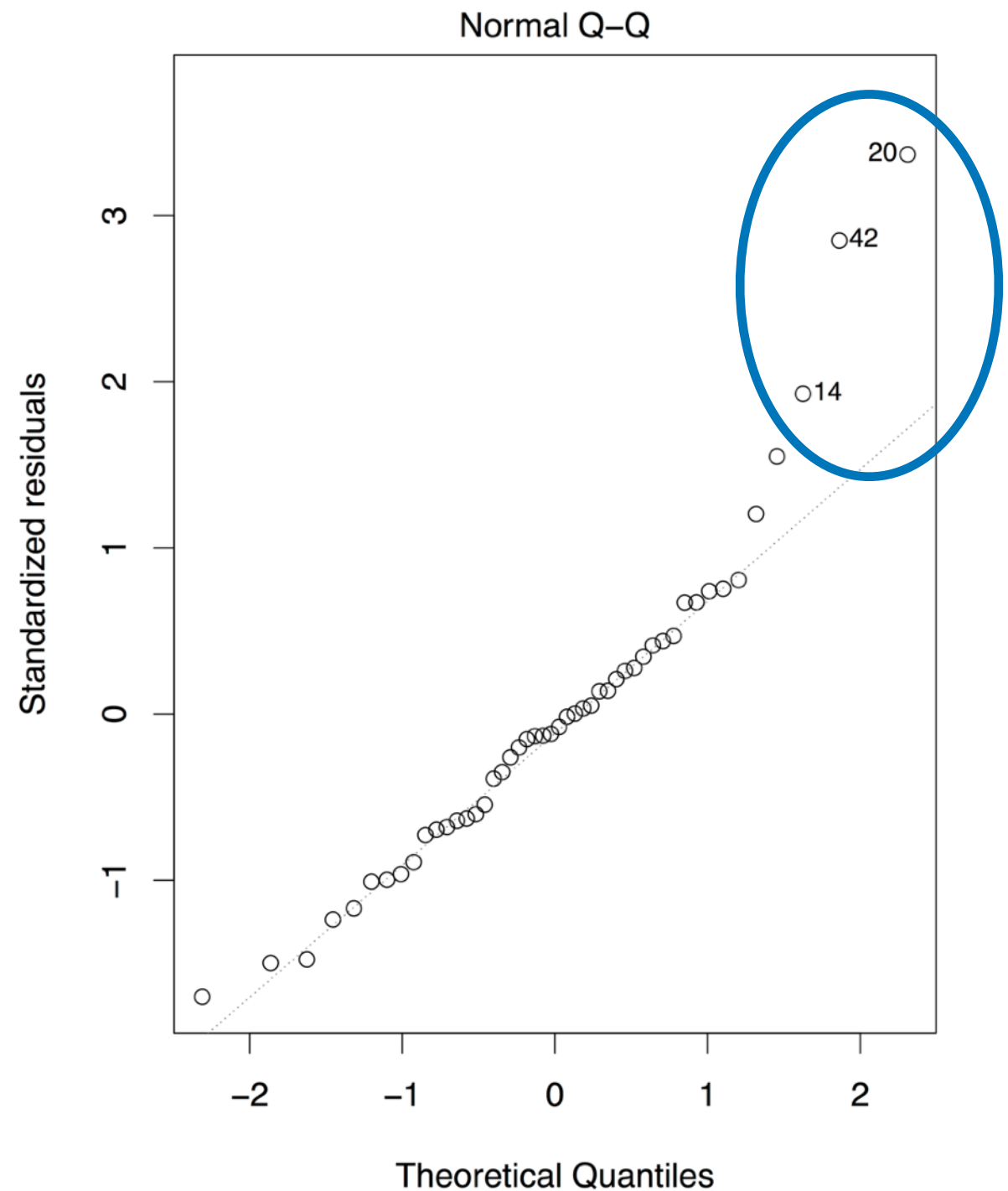
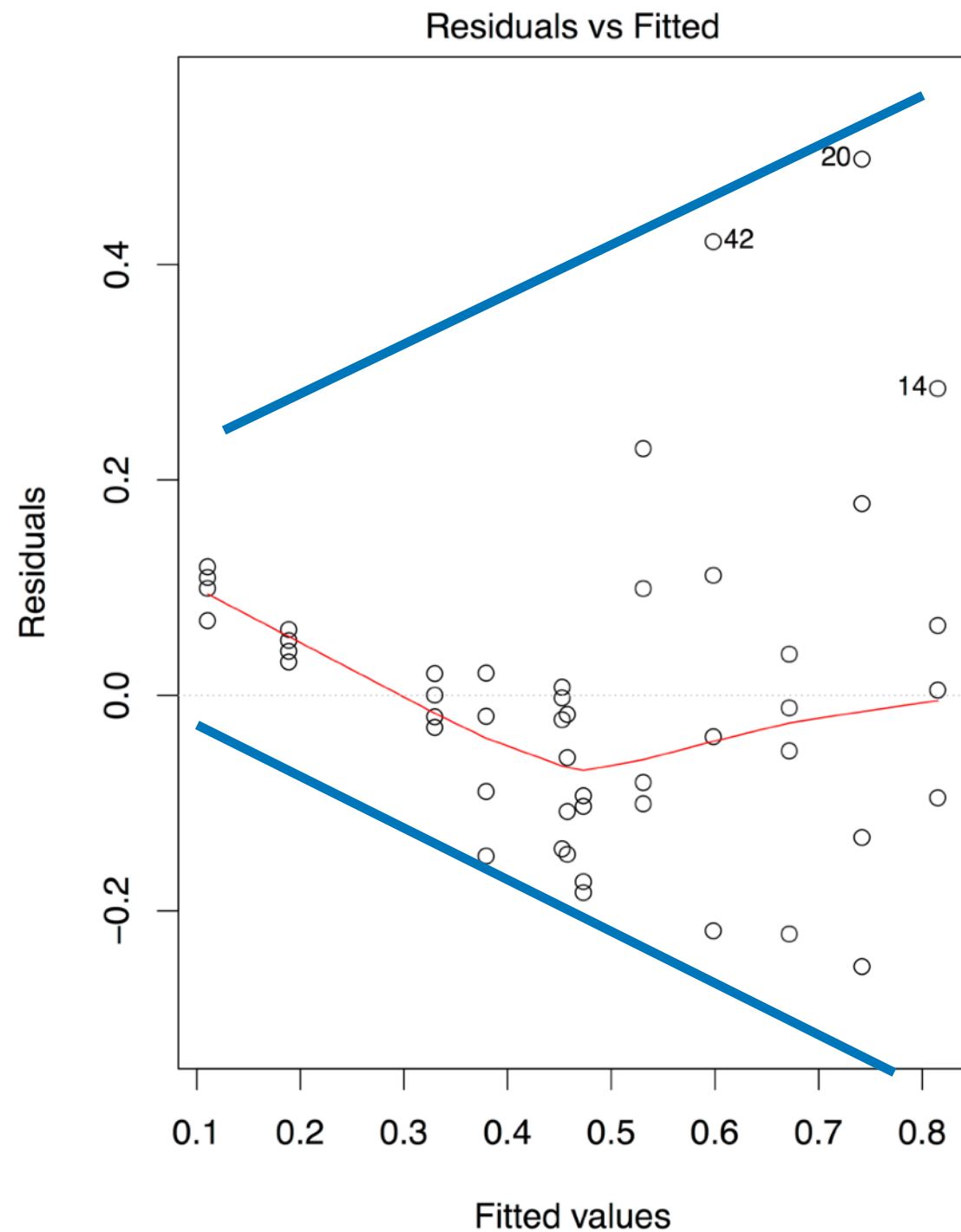
95% family-wise confidence level



Differences in mean levels of Treatment

# Two-way ANOVA

Residual analysis, model  $\text{Time} \sim \text{Poison} + \text{Treatment}$



## Transformations

```
> model_log=lm(log(Time) ~ Poison + Treatment, data=poison)
```

```
> anova(aov(model_log))
```

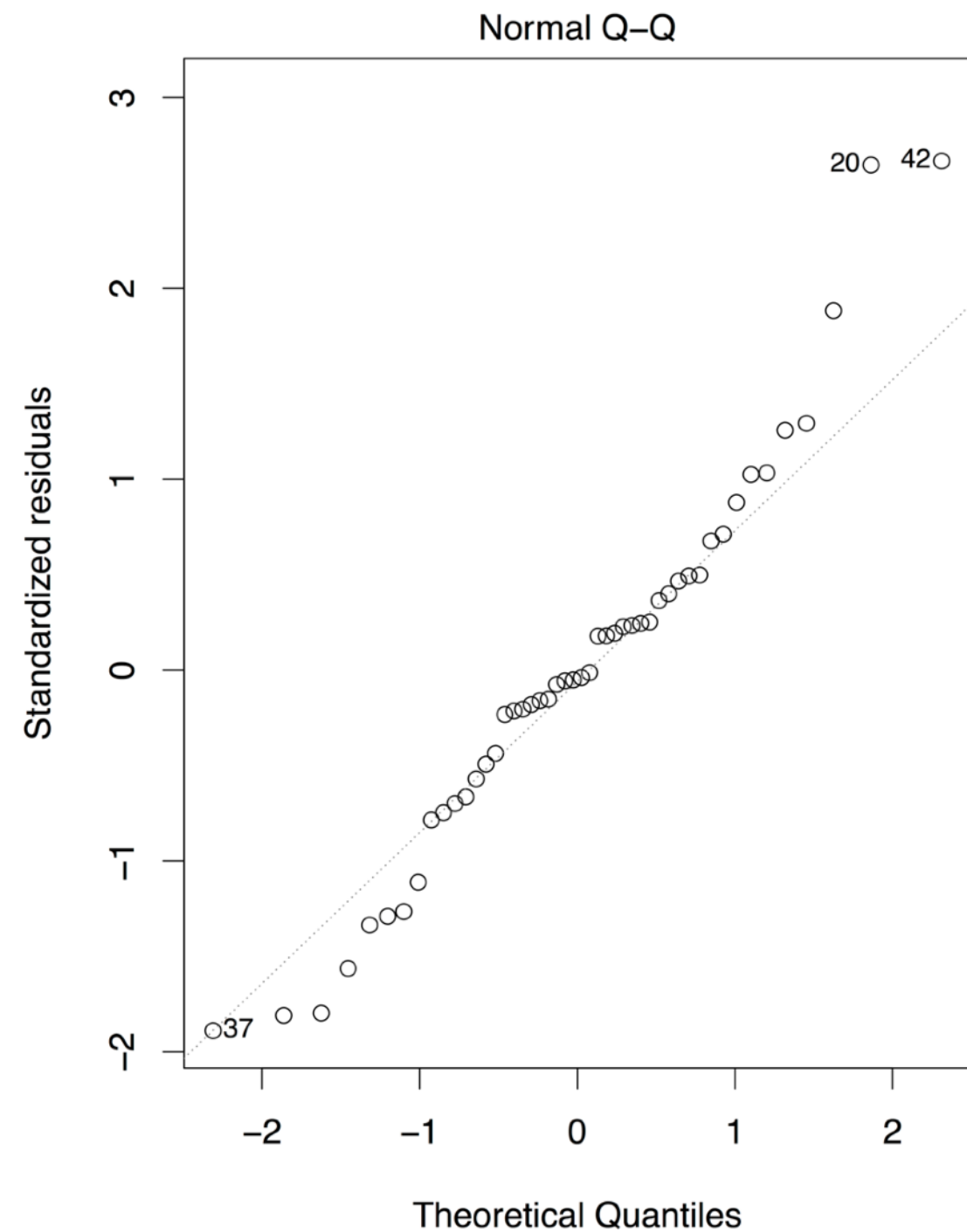
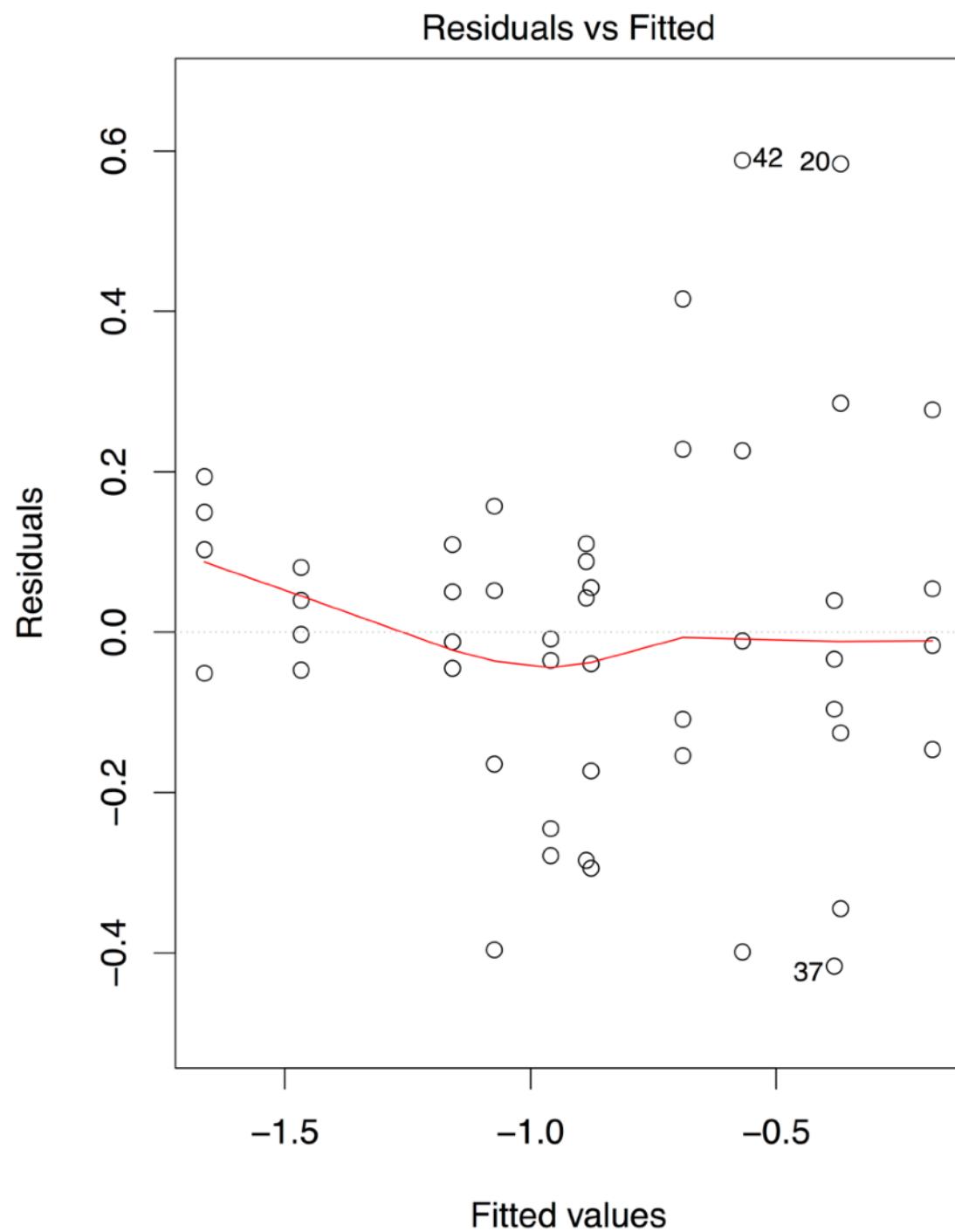
Analysis of Variance Table

Response: log(Time)

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Poison	2	5.2631	2.63156	47.326	1.739e-11
Treatment	3	3.5485	1.18283	21.272	1.550e-08
Residuals	42	2.3354	0.05561		

# Two-way ANOVA

## Transformations



## Transformations

```
> model_reciprocal=lm(1/Time ~ Poison + Treatment,  
data=poison)
```

```
> anova(aov(model_reciprocal))
```

Analysis of Variance Table

Response: 1/Time

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Poison	2	35.064	17.5319	72.683	2.300e-14
Treatment	3	20.341	6.7805	28.110	3.934e-10
Residuals	42	10.131	0.2412		

```
> pdf(file='plot.pdf',pointsize = 18,height=10,width=15)
```

```
> par(mfrow=c(1,2))
```

```
> plot(model_reciprocal,which=1:2)
```

```
> dev.off()
```

# Two-way ANOVA

## Transformations

