

HW#10 Solution (week12 HW)

Due 11/21/2019

HW 24.6 Case Hardening data: CH24PR06.txt

```
HW6 = read.table(url(
  "https://raw.githubusercontent.com/npmladabook/Stat3119/master/Week-12/CH24PR06.txt"))
names(HW6) = c("response", "factorA", "factorB", "factorC", "Units")
HW6$factorA = as.factor(HW6$factorA);
HW6$factorB = as.factor(HW6$factorB)
HW6$factorC = as.factor(HW6$factorC)
str(HW6)
```

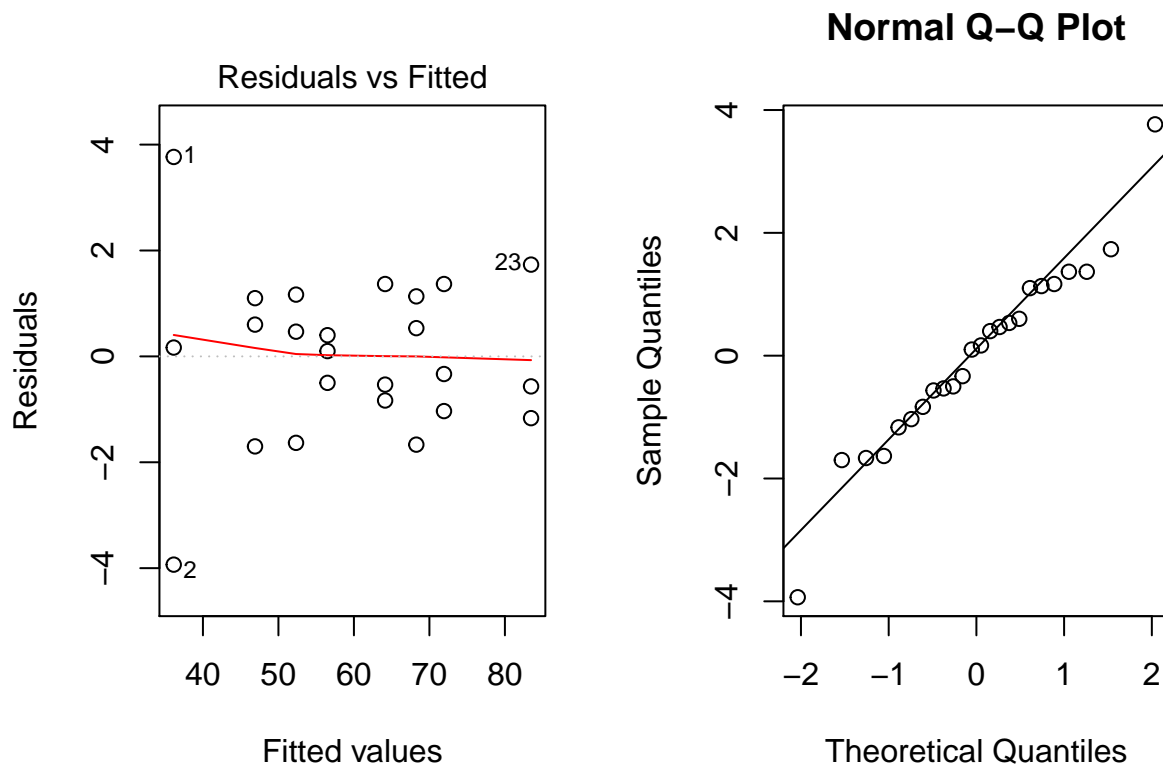
```
## 'data.frame':   24 obs. of  5 variables:
## $ response: num  39.9 32.2 36.3 56 56.9 56.6 53.5 50.7 52.8 70.9 ...
## $ factorA : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...
## $ factorB : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 2 2 2 2 ...
## $ factorC : Factor w/ 2 levels "1","2": 1 1 1 2 2 2 1 1 1 2 ...
## $ Units   : int   1 2 3 1 2 3 1 2 3 1 ...
```

a-b) residuals plots

```
fit <- aov(response ~ factorA * factorB* factorC, data= HW6 )
fit$residuals
```

```
##           1           2           3           4           5           6
## 3.7666667 -3.9333333 0.1666667 -0.5000000 0.4000000 0.1000000
##           7           8           9          10          11          12
## 1.1666667 -1.6333333 0.4666667 -1.0333333 1.3666667 -0.3333333
##          13          14          15          16          17          18
## -1.7000000 1.1000000 0.6000000 1.1333333 -1.6666667 0.5333333
##          19          20          21          22          23          24
## -0.8333333 1.3666667 -0.5333333 -0.5666667 1.7333333 -1.1666667
```

```
par(mfrow=c(1,2))
plot(fit, 1)
#get correlation
QQstat<- qqnorm(fit$residuals) # same as plot(fit, 2)
qqline(fit$residuals)
```



```
paste("The correlation coefficient is", round(cor(QQstat$x, QQstat$y),3))
```

```
## [1] "The correlation coefficient is 0.976"
```

Results: The ANOVA assumptions appear to be reasonable.

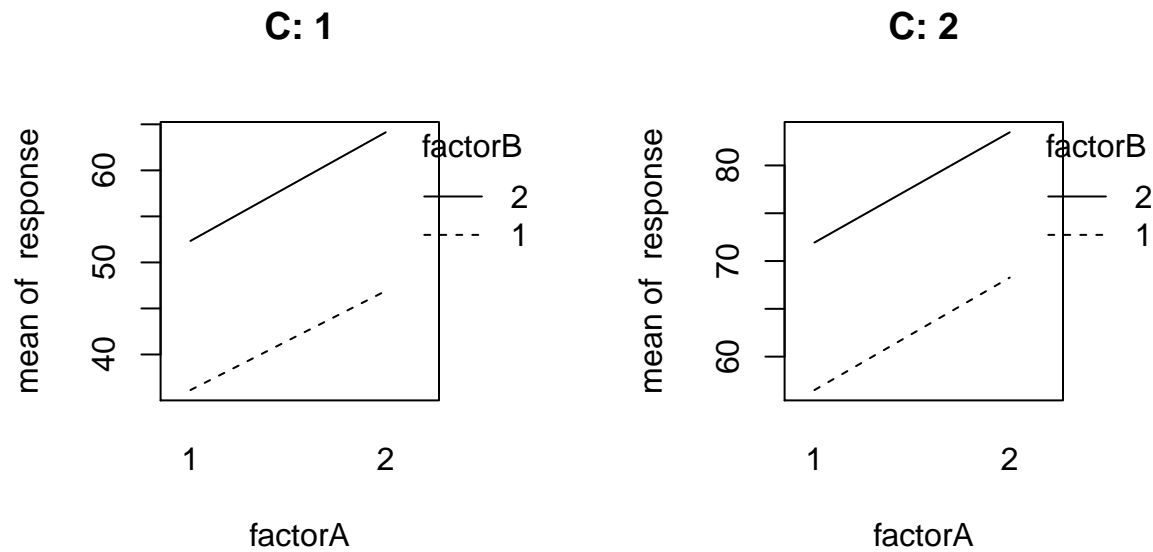
HW 24.7 Case Hardening data

a). Interacton plots

```
par(mfrow= c(1,2), pty="s",mar=c(4,4,5,5))

with( HW6[HW6$factorC=='1'],
  interaction.plot(x.factor = factorA, trace.factor = factorB , response = response,
    main= "C: 1" ) )

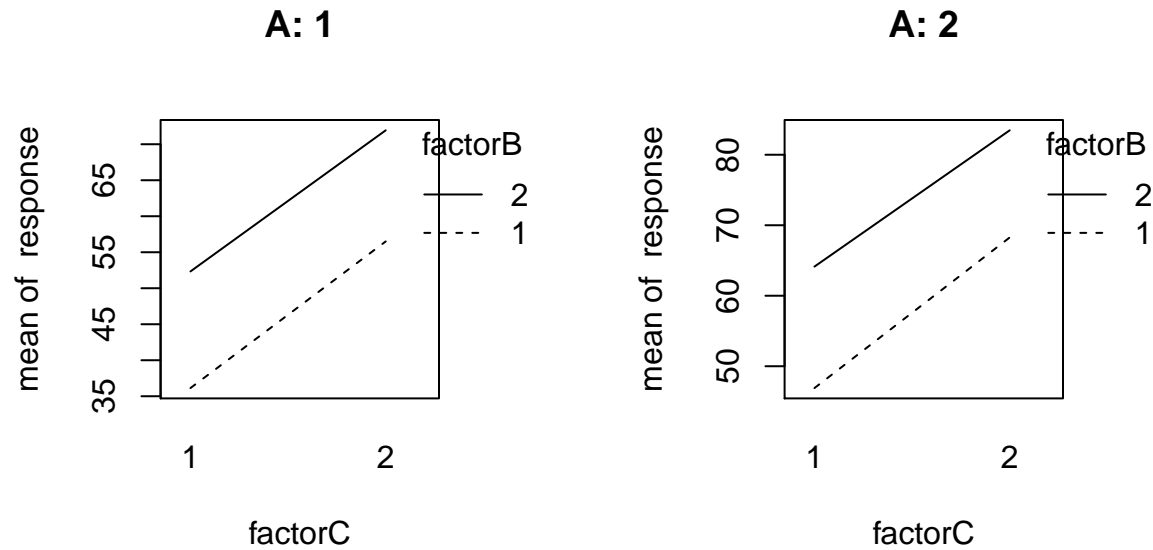
with( HW6[HW6$factorC=='2'],
  interaction.plot(x.factor = factorA, trace.factor = factorB , response = response,
    main= "C: 2" ) )
```



```
par(mfrow= c(1,2),  pty="s",mar=c(4,4,5,5))

with( HW6[HW6$factorA=='1'],,
  interaction.plot(x.factor = factorC, trace.factor = factorB , response = response,
    main= "A: 1" ) )

with( HW6[HW6$factorA=='2'],,
  interaction.plot(x.factor = factorC, trace.factor = factorB , response = response,
    main= "A: 2" ) )
```



b-e). ANOVA analysis

```
summary(fit)
```

```
##               Df Sum Sq Mean Sq F value    Pr(>F)
## factorA         1  788.9    788.9 234.881 5.53e-11 ***
## factorB         1 1539.2   1539.2 458.266 3.35e-13 ***
## factorC         1 2440.2   2440.2 726.510 9.22e-15 ***
## factorA:factorB   1    0.2     0.2  0.071   0.793
## factorA:factorC   1    0.2     0.2  0.060   0.810
## factorB:factorC   1    2.9     2.9  0.875   0.363
## factorA:factorB:factorC 1    0.6     0.6  0.179   0.678
## Residuals       16   53.7     3.4
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Results: From the ANOVA table, P-value column, we can find the interactions (three-way, two way) were not significant. Then main effects were all significant. The test results agree with the findings from the interaction plots.

Detailed solutions for b-e:

c. H_0 : all $(\alpha\beta\gamma)_{ijk}$ equal zero, H_a : not all $(\alpha\beta\gamma)_{ijk}$ equal zero. $F^* = .60167/3.35875 = .18$, $F(.975; 1, 16) = 6.12$. If $F^* \leq 6.12$ conclude H_0 , otherwise H_a . Conclude H_0 . P -value = .68

d. H_0 : all $(\alpha\beta)_{ij}$ equal zero, H_a : not all $(\alpha\beta)_{ij}$ equal zero. $F^* = .24000/3.35875 = .07$, $F(.975; 1, 16) = 6.12$. If $F^* \leq 6.12$ conclude H_0 , otherwise H_a . Conclude H_0 . P -value = .79

H_0 : all $(\alpha\gamma)_{ik}$ equal zero, H_a : not all $(\alpha\gamma)_{ik}$ equal zero. $F^* = .20167/3.35875 = .06$, $F(.975; 1, 16) = 6.12$. If $F^* \leq 6.12$ conclude H_0 , otherwise H_a . Conclude H_0 . P -value = .81

H_0 : all $(\beta\gamma)_{jk}$ equal zero, H_a : not all $(\beta\gamma)_{jk}$ equal zero. $F^* = 2.94000/3.35875 = .875$, $F(.975; 1, 16) = 6.12$. If $F^* \leq 6.12$ conclude H_0 , otherwise H_a . Conclude H_0 . P -value = .36

e. H_0 : all α_i equal zero ($i = 1, 2$), H_a : not all α_i equal zero. $F^* = 788.90667/3.35875 = 234.88$, $F(.975; 1, 16) = 6.12$. If $F^* \leq 6.12$ conclude H_0 , otherwise H_a . Conclude H_a . P -value = 0+

H_0 : all β_j equal zero ($j = 1, 2$), H_a : not all β_j equal zero. $F^* = 1,539.20167/3.35875 = 458.27$, $F(.975; 1, 16) = 6.12$. If $F^* \leq 6.12$ conclude H_0 , otherwise H_a . Conclude H_a . P -value = 0+

H_0 : all γ_k equal zero ($k = 1, 2$), H_a : not all γ_k equal zero. $F^* = 2,440.1667/3.35875 = 726.51$, $F(.975; 1, 16) = 6.12$. If $F^* \leq 6.12$ conclude H_0 , otherwise H_a . Conclude H_a . P -value = 0+

f). Kimball inequality

```
1- (1-0.025)^7
```

```
## [1] 0.1624084
```

Results: $\alpha \leq 0.1624$.

HW 24.8 Inference.

Solution: apply standard formula in this chapter

- a. $\hat{D}_1 = 65.69167 - 54.22500 = 11.46667$, $\hat{D}_2 = 67.96667 - 51.95000 = 16.01667$
 $\hat{D}_3 = 70.04167 - 49.87500 = 20.16667$, $MSE = 3.35875$,
 $s\{\hat{D}_i\} = .7482$ ($i = 1, 2, 3$), $B = t(.99167; 16) = 2.673$
- $$\begin{array}{ll} 11.46667 \pm 2.673(.7482) & 9.467 \leq D_1 \leq 13.467 \\ 16.01667 \pm 2.673(.7482) & 14.017 \leq D_2 \leq 18.017 \\ 20.16667 \pm 2.673(.7482) & 18.167 \leq D_3 \leq 22.167 \end{array}$$
- b. $\bar{Y}_{222} = 83.46667$, $s\{\bar{Y}_{222}\} = 1.0581$, $t(.975; 16) = 2.120$,
 $83.46667 \pm 2.120(1.0581)$, $81.2235 \leq \mu_{222} \leq 85.7098$

R implementation (a)

```
# paired difference : use emmeans to get the estimate and SE, or use formula
```

```
library(emmeans)
Est.meanA <- emmeans(fit, ~ factorA)
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
Est.meanB <- emmeans(fit, ~ factorB)
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
Est.meanC <- emmeans(fit, ~ factorC)
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
L = list( L= c( -1, 1))    #L= mu2-mu1
# Bonferroni methods, alpha=0.05/3
confint(contrast(Est.meanA, L, adjust='none'), level=(1-0.05/3))
```

```
## contrast estimate    SE df lower.CL upper.CL
## L                   11.5 0.748 16      9.47     13.5
##
## Results are averaged over the levels of: factorB, factorC
## Confidence level used: 0.983333333333333
```

```
confint(contrast(Est.meanB, L, adjust='none'), level=(1-0.05/3))
```

```
## contrast estimate    SE df lower.CL upper.CL
## L                16 0.748 16      14      18
##
## Results are averaged over the levels of: factorA, factorC
## Confidence level used: 0.983333333333333
```

```
confint(contrast(Est.meanC, L, adjust='none'), level=(1-0.05/3))
```

```
## contrast estimate    SE df lower.CL upper.CL
## L                20.2 0.748 16      18.2      22.2
##
## Results are averaged over the levels of: factorA, factorB
## Confidence level used: 0.983333333333333
```

R implementation (b)

```
predict(fit, newdata = data.frame(factorA = '2', factorB = '2', factorC = '2' ),
        interval = "confidence", level = .95)
```

```
##          fit          lwr          upr
## 1 83.46667 81.22359 85.70975
```

HW 24.15

```
HW6B = HW6[-(7:8),]
dim(HW6B)
```

```
## [1] 22  5
```

Solutions for a) to d):

$$\text{a. } Y_{ijkm} = \mu_{...} + \alpha_1 X_{ijk1} + \beta_1 X_{ijk2} + \gamma_1 X_{ijk3} + (\alpha\beta)_{11} X_{ijk1} X_{ijk2} + (\alpha\gamma)_{11} X_{ijk1} X_{ijk3} \\ + (\beta\gamma)_{11} X_{ijk2} X_{ijk3} + (\alpha\beta\gamma)_{111} X_{ijk1} X_{ijk2} X_{ijk3} + \epsilon_{ijkm}$$

$$X_{ijk1} = \begin{cases} 1 & \text{if case from level 1 for factor A} \\ -1 & \text{if case from level 2 for factor A} \end{cases}$$

$$X_{ijk2} = \begin{cases} 1 & \text{if case from level 1 for factor B} \\ -1 & \text{if case from level 2 for factor B} \end{cases}$$

$$X_{ijk3} = \begin{cases} 1 & \text{if case from level 1 for factor C} \\ -1 & \text{if case from level 2 for factor C} \end{cases}$$

$$\text{b. } Y_{ijkm} = \mu_{...} + \beta_1 X_{ijk2} + \gamma_1 X_{ijk3} + (\alpha\beta)_{11} X_{ijk1} X_{ijk2} + (\alpha\gamma)_{11} X_{ijk1} X_{ijk3} \\ + (\beta\gamma)_{11} X_{ijk2} X_{ijk3} + (\alpha\beta\gamma)_{111} X_{ijk1} X_{ijk2} X_{ijk3} + \epsilon_{ijkm}$$

c. Full model:

$$\hat{Y} = 60.01667 - 5.67500X_1 - 8.06667X_2 - 10.02500X_3 + .04167X_1X_2 \\ + .15000X_1X_3 - .40833X_2X_3 + .10000X_1X_2X_3,$$

$$SSE(F) = 49.4933$$

Reduced model:

$$\hat{Y} = 61.15167 - 9.20167X_2 - 8.89000X_3 - 1.09333X_1X_2 + 1.28500X_1X_3 \\ - 1.54333X_2X_3 - 1.03500X_1X_2X_3,$$

$$SSE(R) = 667.8413$$

$$H_0: \alpha_1 = 0, H_a: \alpha_1 \neq 0.$$

$$F^* = (618.348/1) \div (49.4933/14) = 174.91, F(.975; 1, 14) = 6.298.$$

If $F^* \leq 6.298$ conclude H_0 , otherwise H_a . Conclude H_a . $P\text{-value} = 0+$

$$\text{d. } \hat{D} = \hat{\mu}_{2..} - \hat{\mu}_{1..} = \hat{\alpha}_2 - \hat{\alpha}_1 = -2\hat{\alpha}_1 = 11.35000, s^2\{\hat{\alpha}_1\} = .18413, s\{\hat{D}\} = .8582, \\ t(.975; 14) = 2.145,$$

$$11.35000 \pm 2.145(.8582), 9.509 \leq D \leq 13.191$$

R implementation a)-d)

```
Ind.A = (HW6B$factorA=="1")*1+ (HW6B$factorA=="2")*(-1)
Ind.B = (HW6B$factorB=="1")*1+ (HW6B$factorB=="2")*(-1)
Ind.C = (HW6B$factorC=="1")*1+ (HW6B$factorC=="2")*(-1)
```

```
Model.full = lm(response~ Ind.A*Ind.B*Ind.C, data= HW6B )
summary(Model.full)
```

##


```
## Call:
## lm(formula = response ~ Ind.A * Ind.B * Ind.C, data = HW6B)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.9333 -0.7667  0.0500  0.9750  3.7667
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    60.01667    0.42910  139.866 < 2e-16 ***
## Ind.A          -5.67500    0.42910  -13.225 2.66e-09 ***
## Ind.B          -8.06667    0.42910  -18.799 2.49e-11 ***
## Ind.C         -10.02500    0.42910  -23.363 1.30e-12 ***
## Ind.A:Ind.B      0.04167    0.42910   0.097  0.924
## Ind.A:Ind.C      0.15000    0.42910   0.350  0.732
## Ind.B:Ind.C     -0.40833    0.42910  -0.952  0.357
## Ind.A:Ind.B:Ind.C 0.10000    0.42910   0.233  0.819
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.88 on 14 degrees of freedom
## Multiple R-squared:  0.9894, Adjusted R-squared:  0.9842
## F-statistic: 187.4 on 7 and 14 DF,  p-value: 9.674e-13
```

```
Model.reduced = lm(response ~ Ind.B*Ind.C + Ind.A:Ind.B + Ind.A:Ind.C + Ind.A:Ind.B:Ind.C, data= HW6B )
summary(Model.reduced)
```

```
##
## Call:
## lm(formula = response ~ Ind.B * Ind.C + Ind.A:Ind.B + Ind.A:Ind.C +
##      Ind.A:Ind.B:Ind.C, data = HW6B)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.620  -4.423   2.857   4.807   6.273
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    61.152    1.492  40.986 < 2e-16 ***
## Ind.B          -9.202    1.492  -6.167 1.80e-05 ***
## Ind.C          -8.890    1.492  -5.958 2.62e-05 ***
## Ind.B:Ind.C     -1.543    1.492  -1.034  0.317
## Ind.B:Ind.A     -1.093    1.492  -0.733  0.475
## Ind.C:Ind.A      1.285    1.492   0.861  0.403
## Ind.B:Ind.C:Ind.A -1.035    1.492  -0.694  0.498
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.673 on 15 degrees of freedom
## Multiple R-squared:  0.8575, Adjusted R-squared:  0.8005
## F-statistic: 15.05 on 6 and 15 DF,  p-value: 1.389e-05
```

```
anova(Model.reduced, Model.full )

## Analysis of Variance Table
##
## Model 1: response ~ Ind.B * Ind.C + Ind.A:Ind.B + Ind.A:Ind.C + Ind.A:Ind.B:Ind.C
## Model 2: response ~ Ind.A * Ind.B * Ind.C
##   Res.Df    RSS Df Sum of Sq    F    Pr(>F)
## 1      15 667.84
## 2      14  49.49   1    618.35 174.91 2.66e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

d) inference for factor A

Approach 1:

1) use formula (24.48a,b,c, page 1021)

```
# For A1: the treatment means are 36.13, 56.5, 52.8, 71.93
# For A2: the treatment means 46.90000 68.26667 64.13333 83.46667

(EstA1 = mean(Model.full$fitted.values[c(1,4,7,8)]))
```

```
## [1] 54.34167
```

```
(EstA2 = mean(Model.full$fitted.values[c(11,14,17,20)]))
```

```
## [1] 65.69167
```

```
# the paired difference
(Diff=EstA2 - EstA1)
```

```
## [1] 11.35
```

2) get SE estimate

```
# The square root of MSE=sigma= 1.88
sigma= 1.88
(SE = sigma/(2*2)*sqrt((1/3+1)+(1/3+1/3)+ (1/3+1/3) +(1/3+1/3)))
```

```
## [1] 0.8580987
```

3) get CI

```
df= nrow(HW6B)- 8 #14=n_T-8

(t.value = qt(.975, df))
```

```
## [1] 2.144787
```

```
LCI= Diff- t.value*SE
UCI= Diff+ t.value*SE

paste(" Then 95% CI is (", round(LCI,4), "-", round(UCI,4),").")
```

```
## [1] " Then 95% CI is ( 9.5096 - 13.1904 )."
```

Approach 2: use the fact that

$$D = \mu_{2..} - \mu_{1..} = \alpha_2 - \alpha_1 = (-\alpha_1) - \alpha_1 = -2\alpha_1.$$

- From the regression output for the full model, $\hat{\alpha}_1 = -5.67500$, then the $\hat{D} = -2 * (-5.675) = 11.35$.
- From the regression output for the full model, $\sigma(\hat{\alpha}_1) = 0.4291$, then the $\sigma(\hat{D}) = 2 * \sigma(\hat{\alpha}_1) = 2 * (0.4291) = 0.8582$.

Approach 3: use emmeans

```
LM.full2 = lm( response~ factorA* factorB* factorC, data=HW6B )
fit.emm <- emmeans( LM.full2, ~ factorA)
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
L = list( L= c( -1, 1))    #L= mu2-mu1

# Bonferroni methods, alpha=0.05/3
confint(contrast(fit.emm, L, adjust='none'))
```

```
## contrast estimate      SE df lower.CL upper.CL
## L               11.3 0.858 14      9.51     13.2
##
## Results are averaged over the levels of: factorB, factorC
## Confidence level used: 0.95
```