## 1 $2^2$ Factorial Design

Q1.1: The data set below is similar to the one we considered in class. Please remember that the labels "low" and "high" are just hypothetical, they reflect upon the geometrical structure of the factorial design.

A	B	Yates notation	Replicates			Total
			I	II	III	
_	_	(1)	28	25	27	80
+	_	(a)	36	32	32	100
_	+	(b)	18	19	23	60
+	+	(ab)	31	30	29	90

(a) Fill out the interaction table:

(b) Show that the main effect of A is equal to

$$A = \frac{1}{2n}((ab) + (a) - (1) - (b)),$$

and compute its value for the given data.

This expression can be derived from the column of A in the interaction table. The corresponding effects are taken with plus or minus, and then divided by the number of observations in each treatment group:

$$A = (-(1) + (a) - (b) + (ab))/(2n) = ((ab) + (a) - (1) - (b))/(2n).$$

There were 2n combinations with A and 2n combinations without A.

(c) Show that:

$$A = \bar{y}_{A+} - \bar{y}_{A-}, \qquad B = \bar{y}_{B+} - \bar{y}_{B-}.$$

Because  $\bar{y}_{A+}$  is the average of the observations which were treated with A and  $\bar{y}_{A-}$  is the average of the observations which were treated without A, the equation is simply a rewriting of A effect in Yates notation.

(d) Using the columns of the interaction table, compute the interaction effect AB for the given data. The equation for AB in Yates notation was given in Lecture 11. It can also be derived using the last column of the interaction table above:

$$AB = ((1) + (ab))/(2n) - ((a) - (b))/(2n).$$

For the given data: (1) = 80, (ab) = 90, (a) = 100, (b) = 60, n = 3. Therefore,

$$AB = (80 + 90 - 100 - 60)/6 = \frac{10}{6} \frac{approx 1.67}{approx 1.67}$$

(e) Fit the interaction model in R and compare the coefficient estimates with your calculations.

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(f) Change the contrasts to options(contrasts=c("contr.sum", "contr.poly")) and fit the model again. Compare the effects estimates from the output with the effects estimates you obtained from Yates formulas. What do you notice?

```
my.data <- NULL
my.data\$A < -as.factor(rep(c(-1,1,-1,1), each = 3))
my.data$B \leftarrow as.factor(rep(c(-1,-1,1,1), each = 3))
my.data$yield <- c(28,25,27,36,32,32,18,19,23,31,30,29)
my.data <- as.data.frame(my.data)</pre>
lm1 \leftarrow lm(yield ~A + B + A*B, data = my.data)
anova(lm1)
## Analysis of Variance Table
## Response: yield
           Df Sum Sq Mean Sq F value
            1 208.333 208.333 53.1915 8.444e-05 ***
## A
             1 75.000 75.000 19.1489 0.002362 **
           1 8.333 8.333 2.1277 0.182776
## A:B
## Residuals 8 31.333 3.917
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
summary(lm1)
##
## lm(formula = yield ~ A + B + A * B, data = my.data)
##
## Residuals:
## Min 1Q Median
                         3Q
                               Max
## -2.000 -1.333 -0.500 1.083 3.000
##
## Coefficients:
      Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 26.667 1.143 23.338 1.21e-08 ***
## A1
              6.667
                          1.616 4.126 0.00332 **
## B1
               -6.667
                          1.616 -4.126 0.00332 **
                3.333
                          2.285 1.459 0.18278
## A1:B1
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 1.979 on 8 degrees of freedom
## Multiple R-squared: 0.903, Adjusted R-squared: 0.8666
## F-statistic: 24.82 on 3 and 8 DF, p-value: 0.0002093
## to change the contrasts:
options(contrasts=c("contr.sum", "contr.poly"))
lm2 \leftarrow lm(yield \sim A + B + A*B, data = my.data)
anova(lm2)
```

```
## Analysis of Variance Table
##
## Response: yield
##
            Df Sum Sq Mean Sq F value
                                          Pr(>F)
## A
             1 208.333 208.333 53.1915 8.444e-05 ***
             1 75.000 75.000 19.1489 0.002362 **
## B
             1
                 8.333
                         8.333 2.1277 0.182776
## Residuals 8 31.333
                         3.917
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
summary(lm2)
##
## Call:
## lm(formula = yield ~ A + B + A * B, data = my.data)
## Residuals:
##
     Min
            1Q Median
                           3Q
                                 Max
## -2.000 -1.333 -0.500 1.083 3.000
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 27.5000
                        0.5713 48.135 3.84e-11 ***
## A1
               -4.1667
                           0.5713
                                  -7.293 8.44e-05 ***
                2.5000
                                    4.376 0.00236 **
## B1
                           0.5713
## A1:B1
                0.8333
                           0.5713
                                    1.459 0.18278
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 1.979 on 8 degrees of freedom
## Multiple R-squared: 0.903, Adjusted R-squared: 0.8666
## F-statistic: 24.82 on 3 and 8 DF, p-value: 0.0002093
```

The option "contrasts" specifies the form in which estimated model effects are presented in the model output. For example, in the default R coding (treatment coding), the intercept is the average value of observations at the baseline (reference level) of each variable in the model. In our context, it is equal to  $(1)/3 = 80/3 \approx 26.6667$ . Each effect is the difference in averages with respect to the reference category. For example, in the output, the A-effect is the average difference  $((a) - (1))/3 = (100 - 80)/3 \approx 6.6667$  and so on.

If the "contr.sum" contrast is selected, the intercept is the total mean through all observations: (80+100+60+90)/12 = 27.5. Each effect is the difference with respect to this total. For example,  $A = (100+90)/6 - 27.5 \approx 4.166667$ .

Notice that the ANOVA table is the same in both cases.

## 2 2<sup>3</sup> Factorial Design

## Q2.1:

Consider the  $2^3$  full factorial design, with two replicates per treatment combination.

- (a) Let A, B, C denote the treatment indicators. The observed data for all treatment combinations are given in the R script below.
- (b) Compute the interaction table for this design.
- (c) By hand (calculator allowed), using the columns of this table, obtain the estimates of all seven effects according to Yates.
- (d) Fit a linear regression model with A, B,C as explanatory variables, with all interactions included.
- (e) Compare the estimates for model coefficients with the effect estimates according to Yates.

The interaction table for the  $2 \times 2 \times 2$  design was shown and explained in the lecture notes.

```
## Here are the observed data
obs.data <- matrix(c(550, 604, 669, 650, 633, 601,
                       642, 635, 1037, 1052, 749, 868,
                      1075, 1063, 729, 860), byrow = TRUE, ncol=2)
dimnames(obs.data) <- list(c("(1)","a","b","ab","c","ac","bc", "abc"),</pre>
                            c("Rep1","Rep2"))
## the column of totals:
total <- apply(obs.data,1,sum);</pre>
total
## (1)
                b
                    ab
           a
                               ас
                                    bc abo
                           С
## 1154 1319 1234 1277 2089 1617 2138 1589
## Define the columns for the main effects as
A \leftarrow rep(c(-1,1),4)
B \leftarrow rep(c(-1,-1,1,1),2)
C \leftarrow c(rep(-1,4), rep(1,4))
##Using the column multiplication obtain the design table
my.data <- cbind(A,B,C,obs.data,total)</pre>
my.data
        A B C Rep1 Rep2 total
## (1) -1 -1 -1 550
                      604
                            1154
## a
        1 -1 -1 669
                      650
                            1319
## b
       -1
           1 -1 633
                      601
                            1234
## ab
           1 - 1 642
                       635
                            1277
## c
       -1 -1 1 1037 1052
                            2089
        1 -1
              1 749
                       868
                            1617
              1 1075 1063
## bc
       -1
           1
                            2138
## abc 1 1 1 729 860
                           1589
```

```
## Columns corresponding to the interaction effects:
AB <- A*B
AC <- A*C
BC <- B*C
ABC <- A*B*C
## the big matrix we obtained during the lecture (the column for the intercept not included)
M <- cbind(A, B, C, AB, AC, BC, ABC)
n \leftarrow 2 # the number of replicates
## Effect estimates are equal to the differences of averages of 4 means
eff.A <- (total %*% A)/(4*n)
eff.B <- (total %*\% B)/(4*n)
eff.C <- (total %*\% C)/(4*n)
eff.AB <- (total %*% AB)/(4*n)
eff.AC <- (total %*\% AC)/(4*n)
eff.BC <- (total %*\% BC)/(4*n)
eff.ABC \leftarrow (total %*% ABC)/(4*n)
all.effects <- t(total)%*% cbind(A,B,C,AB,AC,BC,ABC)/(4*n)
M.complete <- rbind(M,all.effects)</pre>
M.complete
##
                Α
                      В
                             C
                                     AB
                                             AC
                                                     BC
                                                            ABC
## [1,]
         -1.000 -1.000 -1.000 1.000 1.000 1.000 -1.000
##
   [2,]
           1.000 -1.000 -1.000 -1.000
                                           -1.000 1.000 1.000
## [3,]
          -1.000 1.000 -1.000 -1.000 1.000 -1.000
## [4,]
          1.000 1.000 -1.000 1.000
                                          -1.000 -1.000 -1.000
          -1.000 -1.000
                                 1.000
                                          -1.000 -1.000 1.000
## [5,]
                         1.000
## [6,]
           1.000 -1.000
                         1.000 -1.000
                                           1.000 -1.000 -1.000
## [7,]
         -1.000 1.000
                         1.000 -1.000
                                         -1.000 1.000 -1.000
## [8,]
          1.000 1.000 1.000 1.000
                                         1.000 1.000 1.000
## [9,] -101.625 7.375 306.125 -24.875 -153.625 -2.125 5.625
## to fit a linear regression model:
M1 \leftarrow rbind(M[,1:3],M[,1:3])
dat <- cbind(M1,as.vector(obs.data))</pre>
dat <- as.data.frame(dat)</pre>
colnames(dat) <- c("A", "B", "C", "Response")</pre>
options(contrasts=c("contr.treatment","contr.poly"))
mod1 <- lm(Response ~ A*B*C, data = dat)</pre>
summary(mod1)
##
## Call:
## lm(formula = Response ~ A * B * C, data = dat)
## Residuals:
```

```
## Min 1Q Median 3Q Max
## -65.50 -11.12 0.00 11.12 65.50
##
## Coefficients:
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 776.062 11.865 65.406 3.32e-12 ***
             -50.812
                         11.865 -4.282 0.002679 **
                         11.865 0.311 0.763911
## B
                3.688
             153.062 11.865 12.900 1.23e-06 ***
-12.437 11.865 -1.048 0.325168
-76.812 11.865 -6.474 0.000193 ***
## C
## A:B
## A:C
                         11.865 -0.090 0.930849
## B:C
               -1.062
## A:B:C
               2.813
                         11.865 0.237 0.818586
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 47.46 on 8 degrees of freedom
## Multiple R-squared: 0.9661, Adjusted R-squared: 0.9364
## F-statistic: 32.56 on 7 and 8 DF, p-value: 2.896e-05
options(contrasts=c("contr.sum","contr.poly"))
mod <- lm(Response ~ A*B*C, data = dat)</pre>
summary(mod)
##
## Call:
## lm(formula = Response ~ A * B * C, data = dat)
##
## Residuals:
## Min 1Q Median
                        3Q
                                Max
## -65.50 -11.12 0.00 11.12 65.50
##
## Coefficients:
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 776.062 11.865 65.406 3.32e-12 ***
## A
              -50.812
                         11.865 -4.282 0.002679 **
## B
                3.688 11.865 0.311 0.763911
## C
             ## A:B
              -12.437
                         11.865 -1.048 0.325168
                       11.865 -6.474 0.000193 ***
## A:C
              -76.812
              -1.062 11.865 -0.090 0.930849
## B:C
## A:B:C
               2.813
                         11.865 0.237 0.818586
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 47.46 on 8 degrees of freedom
## Multiple R-squared: 0.9661, Adjusted R-squared: 0.9364
## F-statistic: 32.56 on 7 and 8 DF, p-value: 2.896e-05
mean(total)/2; coef(mod)[1]
## [1] 776.0625
```

## (Intercept) ## 776.0625