

assignment3_stat453

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2024-03-05

###Question1

```
#a) Analyze the data and determine which factor is not significant.  
A <- c(-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1)  
B <- c(-1,-1,1,1,-1,1,1,-1,-1,1,1,-1,1,1)  
C <- c(-1,-1,-1,-1,1,1,1,-1,-1,-1,1,1,1,1)  
D <- c(-1,-1,-1,-1,-1,-1,-1,1,1,1,1,1,1,1)  
y <- c(2.45,3.36,2.16,2.29,2.49,3.39,2.32,2.44,1.84,2.24,1.69,1.87,2.29,2.92,2.04,2.03)  
data <- data.frame(A,B,C,D,y)
```

```
model <- lm(y ~ A*B*C*D , data = data)  
#fullnormal(coef(model)[-1],alpha=.025)
```

```
#Prepare an ANOVA table  
anova_table <- anova(model)
```

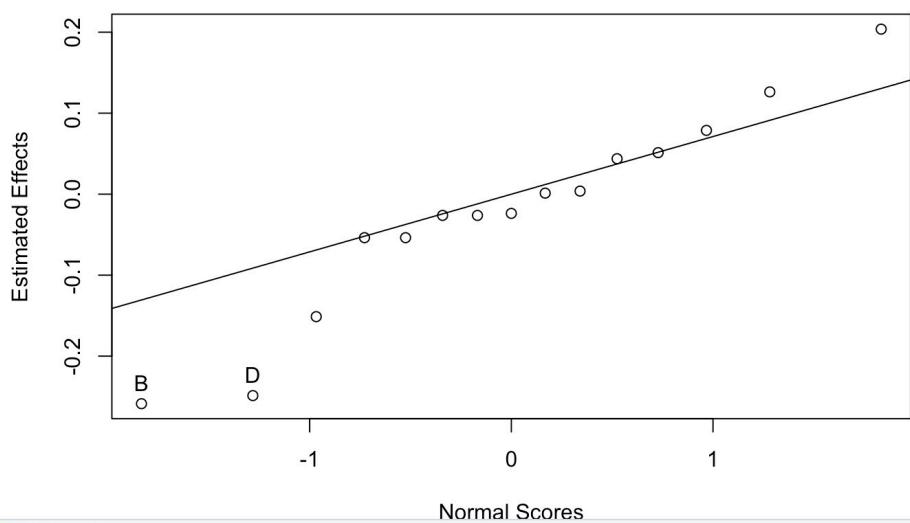
```
## Warning in anova.lm(model): ANOVA F-tests on an essentially perfect fit are  
## unreliable
```

```
# Display the ANOVA table  
print(anova_table)
```

```
## Analysis of Variance Table  
##  
## Response: y  
##             Df Sum Sq Mean Sq F value Pr(>F)  
## A            1 0.66423 0.66423   NaN   NaN  
## B            1 1.07122 1.07122   NaN   NaN  
## C            1 0.25502 0.25502   NaN   NaN  
## D            1 0.99002 0.99002   NaN   NaN  
## A:B          1 0.36603 0.36603   NaN   NaN  
## A:C          1 0.00002 0.00002   NaN   NaN  
## B:C          1 0.00903 0.00903   NaN   NaN  
## A:D          1 0.04623 0.04623   NaN   NaN  
## B:D          1 0.04202 0.04202   NaN   NaN  
## C:D          1 0.09922 0.09922   NaN   NaN  
## A:B:C        1 0.01102 0.01102   NaN   NaN
```



Normal Q-Q Plot



Chunk 2 ▾

R Markdown ▾

```
#e) Confound the projected design with blocks using the highest order interaction  
#as a confounding. Write down the runs for both blocks and estimate the block  
#effect. What is the block effect really estimating in this case?  
  
# Create a new factor "Block"  
data$Block <- ifelse(data$A * data$B * data$D > 0, "1", "2")  
  
# Fit the model with the block factor  
lm_block <- lm(y ~ A * B * D + Block, data = data)  
  
# Summary of the model  
summary(lm_block)
```

```
##  
## Call:  
## lm(formula = y ~ A * B * D + Block, data = data)  
##  
## Residuals:  
##      Min      1Q Median      3Q     Max  
## -0.34 -0.08   0.00   0.08   0.34  
##  
## Coefficients: (1 not defined because of singularities)  
##                 Estimate Std. Error t value Pr(>|t|)  
## (Intercept)  2.40750   0.08214 29.310 1.99e-09 ***  
## A          0.20375   0.05808  3.508  0.00798 **  
## B         -0.25875   0.05808 -4.455  0.00213 **  
## D         -0.24875   0.05808 -4.283  0.00268 **  
## Block2    -0.08750   0.11616 -0.753  0.47288  
## A:B       -0.15125   0.05808 -2.604  0.03142 *  
## A:D       -0.05375   0.05808 -0.925  0.38181  
## B:D       0.05125   0.05808  0.882  0.40330  
## A:B:D      NA       NA       NA       NA  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 0.2323 on 8 degrees of freedom  
## Multiple R-squared:  0.8814, Adjusted R-squared:  0.7777  
## F-statistic: 8.497 on 7 and 8 DF,  p-value: 0.003616
```

```
#So i got -0.08750 as the block effect
```

```
###Question2
```

```
# Import the data:  
data = read.csv("yield.csv")  
#
```

```
# Import the data:  
data = read.csv("yield.csv")  
data
```

```
##      A  B  C  D Rep Yield  
## 1 -1 -1 -1 -1   1    90  
## 2  1 -1 -1 -1   1    74  
## 3 -1  1 -1 -1   1    81  
## 4  1  1 -1 -1   1    83  
## 5 -1 -1  1 -1   1    77  
## 6  1 -1  1 -1   1    81  
## 7 -1  1  1 -1   1    88  
## 8  1  1  1 -1   1    73  
## 9 -1 -1 -1  1   1    98  
## 10 1 -1 -1  1   1    72  
## 11 -1  1 -1  1   1    87  
## 12 1  1 -1  1   1    85  
## 13 -1 -1  1  1   1    99  
## 14 1 -1  1  1   1    79  
## 15 -1  1  1  1   1    87  
## 16 1  1  1  1   1    80  
## 17 -1 -1 -1 -1   2    93  
## 18 1 -1 -1 -1   2    78  
## 19 -1  1 -1 -1   2    85  
## 20 1  1 -1 -1   2    80  
## 21 -1 -1  1 -1   2    78  
## 22 1 -1  1 -1   2    80  
## 23 -1  1  1 -1   2    82  
## 24 1  1  1 -1   2    70  
## 25 -1 -1 -1  1   2    95  
## 26 1 -1 -1  1   2    76  
## 27 -1  1 -1  1   2    83  
## 28 1  1 -1  1   2    86  
## 29 -1 -1  1  1   2    90  
## 30 1 -1  1  1   2    75  
## 31 -1  1  1  1   2    84  
## 32 1  1  1  1   2    80
```

```
# Fit a linear model  
model <- lm(Yield ~ A*B*C*D , data = data)  
# (a) Estimate the factor effects  
effects <- 2* coef(model)
```

```
# Display the estimated factor effects
```



```
print(effects)
```

```
## (Intercept)      A       B       C       D     A:B  
## 165.5625    -9.0625   -1.3125  -2.6875  3.9375  4.0625  
## A:C          B:C     A:D     B:D     C:D     A:B:C  
## 0.6875    -0.5625   -2.1875  -0.1875  1.6875  -5.1875  
## A:B:D        A:C:D   B:C:D   A:B:C:D  
## 4.6875    -0.9375   -0.9375   2.4375
```

```
# Based on the R output the estimated factor effects for the 2^4 factorial design is:
```

```
#Intercept: 82.78125, A: -4.53125, B: -0.65625, C: -1.34375, D: 1.96875, A:B: 2.03125, A:C: 0.34375, B:C: -0.28125, A:D: -1.09375, B:D: -0.09375, C:D: 0.84375, A:B:C: -2.59375, A:B:D: 2.34375, A:C:D: -0.46875, B:C:D: -0.46875, A:B:C:D: 1.21875
```

```
# (b) Prepare an ANOVA table  
anova_table <- anova(model)
```

```
# Display the ANOVA table  
print(anova_table)
```

```
## Analysis of Variance Table  
##  
## Response: Yield  
##             Df Sum Sq Mean Sq F value    Pr(>F)  
## A            1 657.03 657.03 85.8163 7.875e-08 ***  
## B            1 13.78  13.78  1.8000 0.1984451  
## C            1 57.78  57.78  7.5469 0.0143171 *  
## D            1 124.03 124.03 16.2000 0.0009794 ***  
## A:B          1 132.03 132.03 17.2449 0.0007491 ***  
## A:C          1   3.78   3.78  0.4939 0.4923019  
## B:C          1   2.53   2.53  0.3306 0.5732962  
## A:D          1  38.28  38.28  5.0000 0.0399447 *  
## B:D          1   0.28   0.28  0.0367 0.8504174  
## C:D          1 22.78  22.78  2.9755 0.1037933  
## A:B:C        1 215.28 215.28 28.1184 7.146e-05 ***  
## A:B:D        1 175.78 175.78 22.9592 0.0001997 ***  
## A:C:D        1   7.03   7.03  0.9184 0.3521621  
## B:C:D        1   7.03   7.03  0.9184 0.3521621  
## A:B:C:D     1  47.53  47.53  6.2082 0.0240766 *  
## Residuals   16 122.50 7.66  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#From the anova table, the p-value of A,C,D,A:B,A:D,A:B:C,A:B:D,A:B:C:D are less than 0.05 = a. So these factors are important factors in this experiment.
```

```
#{(c)ch
model<- lm(Yield ~ A*B*C*D , data = data)
model
```

```
##
## Call:
## lm(formula = Yield ~ A * B * C * D, data = data)
##
## Coefficients:
## (Intercept)          A            B            C            D          A:B
## 82.78125      -4.53125     -0.65625     -1.34375     1.96875    2.03125
## A:C           B:C           A:D           B:D           C:D          A:B:C
## 0.34375      -0.28125     -1.09375     -0.09375     0.84375   -2.59375
## A:B:D         A:C:D         B:C:D         A:B:C:D
## 2.34375      -0.46875     -0.46875     1.21875
```

$\text{Yield} = \beta_0 + \beta_1 A + \beta_3 C + \beta_4 D + \beta_5 AB + \beta_6 AC + \beta_7 AD + \beta_8 BC + \beta_9 BD + \beta_{10} CD + \beta_{11} ABC + \beta_{12} ABD + \beta_{13} ACD + \beta_{14} BCD + \beta_{15} ABCD + \epsilon$

$\text{So, Yield} = 82.78125 - 4.53125A - 0.65625B - 1.34375C + 1.96875D + 2.03125AB - 1.09375AD - 2.59375AC + 2.34375AD + 1.21875ACD + \epsilon$

```
#{(d)

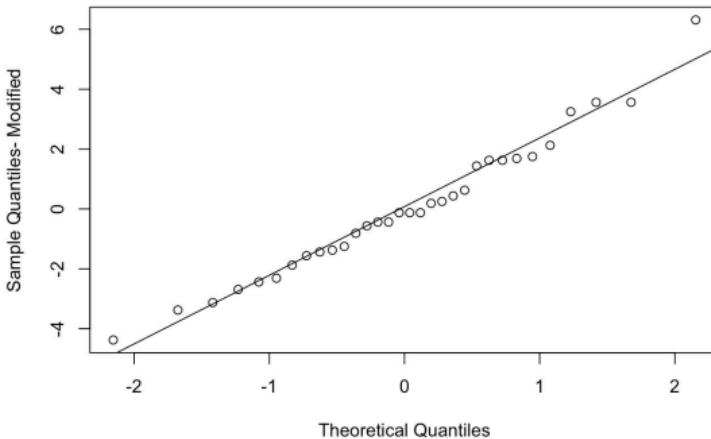
#Final model - remove non-significant terms
res.aov<-aov(Yield~A*B*C*D~A:C~B:D~C:D~A:C:D~B:C:D,data=data)
summary(res.aov)
```

```
##
##              Df Sum Sq Mean Sq F value    Pr(>F)
## A             1  657.0  657.0  87.109 4.17e-09 ***
## B             1   13.8   13.8   1.827 0.190204
## C             1   57.8   57.8   7.661 0.011226 *
## D             1  124.0  124.0  16.444 0.000527 ***
## A:B           1  132.0  132.0  17.505 0.000385 ***
## A:D           1   38.3   38.3   5.075 0.034576 *
## A:B:C         1  215.3  215.3  28.542 2.31e-05 ***
## A:B:D         1  175.8  175.8  23.305 8.01e-05 ***
## A:B:C:D       1   47.5   47.5   6.302 0.019913 *
## Residuals    22  165.9    7.5
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



```
#Residual Analysis  
#Normality  
yield_residuals=res.aov$residuals  
qqnorm(yield_residuals, ylim=c(min(yield_residuals),max(yield_residuals)), main = "Normal Q-Q Plot for Residuals",  
       xlab = "Theoretical Quantiles", ylab = "Sample Quantiles- Modified",  
       plot.it = TRUE, datax = FALSE)  
  
qqline(yield_residuals, datax = FALSE, distribution = qnorm)
```

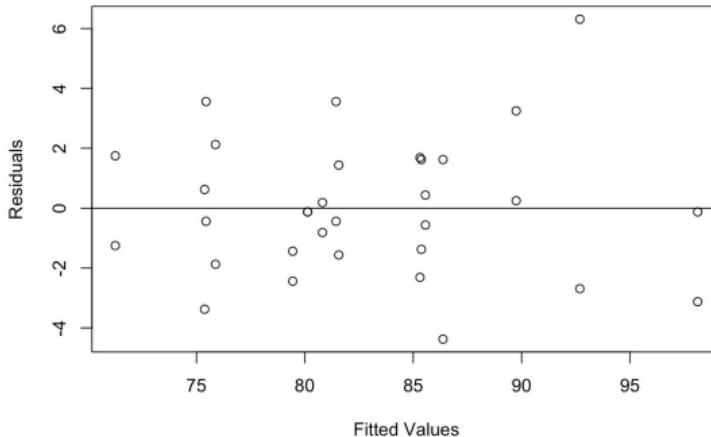
Normal Q-Q Plot for Residuals



```
#Test normality using Shapiro Wilks  
shapiro.test(yield_residuals)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: yield_residuals  
## W = 0.97742, p-value = 0.7219
```

```
#Check Variance  
Fitted_values=res.aov$fitted.values  
plot(Fitted_values,yield_residuals,ylab="Residuals",xlab="Fitted Values")  
abline(h=0)
```



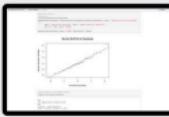
#From the q-q plot for residuals, the almost of all data are near the straight line. Also, by the Shapiro-Wilk test, Since the p-value is greater than 0.05, we fail to reject the null hypothesis that the data is normally distributed.

#it means the distribution is normally distributed.

#Moreover, The residual vs fitted value plot shows
that the pattern of scatter is the almost same.
#so the variance is adequate
#So this is an adequate model to test.

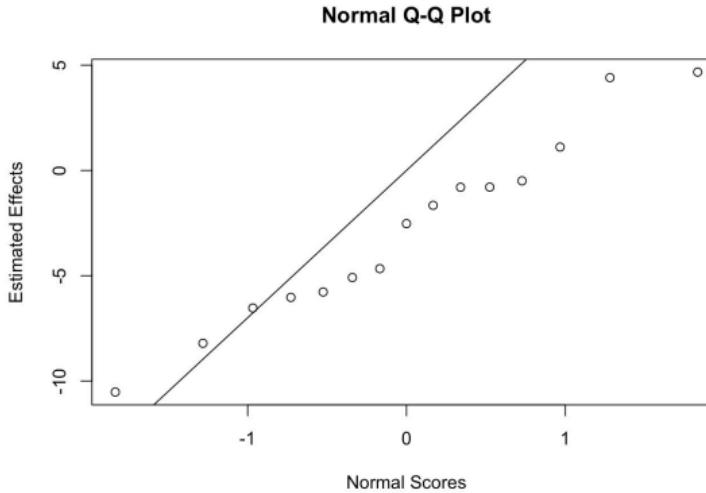
###Question3

a) Are any of the effects significant?

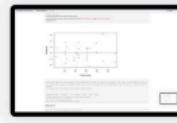


###Question3

```
#a) Are any of the effects significant?  
# Define the effect estimates  
effects <- c(ABCD = -2.5251, AD = -1.6564, BCD = 4.4054, AC = 1.1109,  
ACD = -0.4932, AB = -10.5229, ABD = -5.0842, D = -6.0275,  
ABC = -5.7696, C = -8.2045, CD = 4.6707, B = -6.5304,  
BD = -4.6620, A = -0.7914, BC = -0.7982)  
  
#According to the fullnormal graph, there is no labels.  
#It means that there are no significant effects.  
  
library(daewr)  
fullnormal(effects, alpha=.025)
```

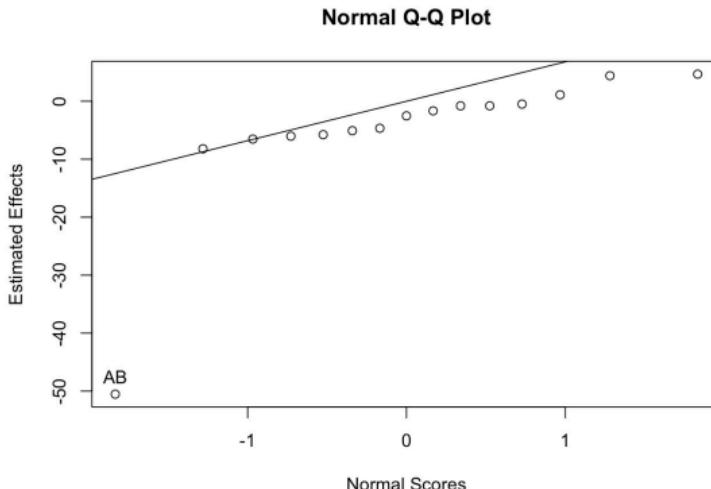


```
#b) What happens if you the effect of the interaction AB was -50.5229 instead of  
-#10.5229?  
effects2 <- c(ABCD = -2.5251, AD = -1.6564, BCD = 4.4054, AC = 1.1109,  
ACD = -0.4932, AB = -50.5229, ABD = -5.0842, D = -6.0275,  
ABC = -5.7696, C = -8.2045, CD = 4.6707, B = -6.5304
```



```
#b) What happens if you the effect of the interaction AB was -50.5229 instead of
#-10.5229?
effects2 <- c(ABCD = -2.5251, AD = -1.6564, BCD = 4.4054, AC = 1.1109,
           ACD = -0.4932, AB = -50.5229, ABD = -5.0842, D = -6.0275,
           ABC = -5.7696, C = -8.2045, CD = 4.6707, B = -6.5304,
           BD = -4.6620, A = -0.7914, BC = -0.7982)

fullnormal(effects2,alpha=.025)
```



#According to the fullnormal graph, there is one label which is AB.
#So, only AB is significant effect.

###Question4

```
#(a) Analyze the data from this experiment. Identify the significant factors  
#and interactions and removing the non-significant terms, when  
#appropriate.
```

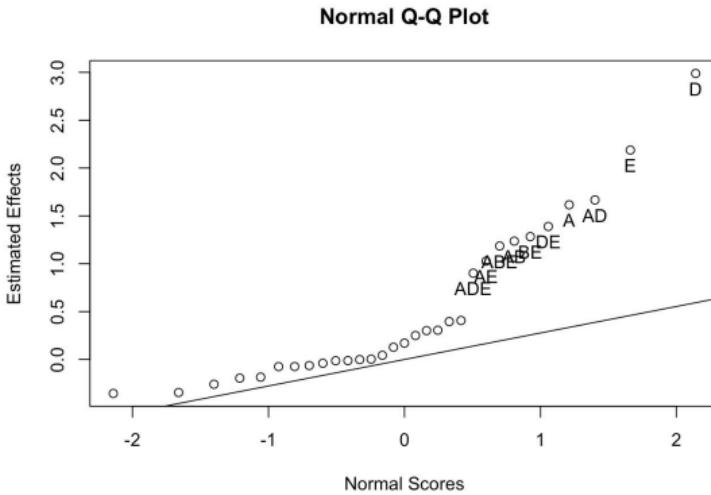
```
C <- c(-1,-1,-1,-1,1,1,1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1,1,1,1,-1,-1,-1,-1,1,1,1)
D <- c(-1,-1,-1,-1,-1,-1,1,1,1,1,1,1,1,-1,-1,-1,-1,-1,-1,-1,1,1,1,1,1,1,1)
E <- c(-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,1,1,1,1,1,1,1)
Obs <- c(8.11,5.56,5.77,5.82,9.17,7.8,3.23,5.69,8.82,14.23,9.2,8.94,8.68,11.49,6.25,9.12,7.93,5,7.47,12,9.86,3.6
5,6.4,11.61,12.43,17.55,8.87,25.38,13.06,18.85,11.78,26.05)
Data <- data.frame(A,B,C,D,E,Obs)
Data
```

```
##      A   B   C   D   E   Obs
## 1 -1 -1 -1 -1 -1  8.11
## 2  1 -1 -1 -1 -1  5.56
## 3 -1  1 -1 -1 -1  5.77
## 4  1  1 -1 -1 -1  5.82
## 5 -1 -1  1 -1 -1  9.17
## 6  1 -1  1 -1 -1  7.80
## 7 -1  1  1 -1 -1  3.23
## 8  1  1  1 -1 -1  5.69
## 9 -1 -1 -1  1 -1  8.82
## 10 1 -1 -1  1 -1 14.23
## 11 -1  1 -1  1 -1  9.20
## 12  1  1 -1  1 -1  8.94
## 13 -1 -1  1  1 -1  8.68
## 14  1 -1  1  1 -1 11.49
## 15 -1  1  1  1 -1  6.25
## 16  1  1  1  1 -1  9.12
## 17 -1 -1 -1 -1  1  7.93
## 18  1 -1 -1 -1  1  5.00
## 19 -1  1 -1 -1  1  7.47
## 20  1  1 -1 -1  1 12.00
## 21 -1 -1  1 -1  1  9.86
## 22  1 -1  1 -1  1  3.65
## 23 -1  1  1 -1  1  6.40
## 24  1  1  1 -1  1 11.61
## 25 -1 -1 -1  1  1 12.43
## 26  1 -1 -1  1  1 17.55
## 27 -1  1 -1  1  1  8.87
## 28  1  1 -1  1  1 25.38
## 29 -1 -1  1  1  1 13.06
## 30  1 -1  1  1  1 18.85
## 31 -1  1  1  1  1 11.78
## 32  1  1  1  1  1 26.05
```

```
Model <- lm(Obs~A*B*C*D*E,data = Data)
coef(Model)
```

$\#$	(Intercept)	A	B	C	D	E
$\#$	10.1803125	1.6159375	0.0434375	-0.0121875	2.9884375	2.1878125
$\#$	A:B	A:C	B:C	A:D	B:D	C:D
$\#$	1.2365625	-0.0015625	-0.1953125	1.6665625	-0.0134375	0.0034375
$\#$	A:E	B:E	C:E	D:E	A:B:C	A:B:D
$\#$	1.0271875	1.2834375	0.3015625	1.3896875	0.2503125	-0.3453125
$\#$	A:C:D	B:C:D	A:B:E	A:C:E	B:C:E	A:D:E
$\#$	-0.0634375	0.3053125	1.1853125	-0.2590625	0.1709375	0.9015625
$\#$	B:D:E	C:D:E	A:B:C:D	A:B:C:E	A:B:D:E	A:C:D:E
$\#$	-0.0396875	0.3959375	-0.0740625	-0.1846875	0.4071875	0.1278125
$\#$	B:C:D:E	A:B:C:D:E				
$\#$	-0.0746875	-0.3553125				

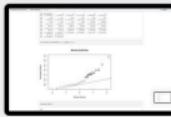
```
fullnormal(coef(Model)[-1],alpha=.025)
```



```
summary(Model)
```

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```
##  
## Call:  
## lm(formula = Obs ~ A * B * C * D * E, data = Data)  
##  
## Residuals:  
## ALL 32 residuals are 0: no residual degrees of freedom!  
##  
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)  
## (Intercept) 10.180312   NaN   NaN   NaN  
## A          1.615938   NaN   NaN   NaN  
## B          0.043438   NaN   NaN   NaN  
## C         -0.012187   NaN   NaN   NaN  
## D          2.988437   NaN   NaN   NaN  
## E          2.187813   NaN   NaN   NaN  
## A:B        1.236562   NaN   NaN   NaN  
## A:C       -0.001563   NaN   NaN   NaN  
## B:C      -0.195313   NaN   NaN   NaN  
## A:D        1.666563   NaN   NaN   NaN  
## B:D      -0.013438   NaN   NaN   NaN  
## C:D        0.003437   NaN   NaN   NaN  
## A:E        1.027188   NaN   NaN   NaN  
## B:E        1.283437   NaN   NaN   NaN  
## C:E        0.301563   NaN   NaN   NaN  
## D:E        1.389687   NaN   NaN   NaN  
## A:B:C     0.250313   NaN   NaN   NaN  
## A:B:D    -0.345312   NaN   NaN   NaN  
## A:C:D    -0.063437   NaN   NaN   NaN  
## B:C:D     0.305312   NaN   NaN   NaN  
## A:B:E     1.185313   NaN   NaN   NaN  
## A:C:E    -0.259062   NaN   NaN   NaN  
## B:C:E     0.170938   NaN   NaN   NaN  
## A:D:E     0.901563   NaN   NaN   NaN  
## B:D:E    -0.039687   NaN   NaN   NaN  
## C:D:E     0.395938   NaN   NaN   NaN  
## A:B:C:D  -0.074063   NaN   NaN   NaN  
## A:B:C:E  -0.184688   NaN   NaN   NaN  
## A:B:D:E   0.407187   NaN   NaN   NaN  
## A:C:D:E   0.127812   NaN   NaN   NaN  
## B:C:D:E  -0.074688   NaN   NaN   NaN  
## A:B:C:D:E -0.355312   NaN   NaN   NaN  
##  
## Residual standard error: NaN on 0 degrees of freedom  
## Multiple R-squared:  1, Adjusted R-squared:  NaN  
## F-statistic:  NaN on 31 and 0 DF, p-value: NA
```



```
Model2 <- aov(Obs~A+B+D+E+A*B+A*D+A*E+B*E+D*E+A*B*E+A*D*E, data = Data)
summary(Model2)
```

```

##          Df Sum Sq Mean Sq F value    Pr(>F)
## A           1   83.56   83.56 51.362 6.10e-07 ***
## B           1     0.06     0.06  0.037 0.849178
## D           1 285.78 285.78 175.664 2.30e-11 ***
## E           1 153.17 153.17  94.149 5.24e-09 ***
## A:B         1   48.93   48.93 30.076 2.28e-05 ***
## A:D         1   88.88   88.88 54.631 3.87e-07 ***
## A:E         1   33.76   33.76 20.754 0.000192 ***
## B:E         1   52.71   52.71 32.400 1.43e-05 ***
## D:E         1   61.80   61.80 37.986 5.07e-06 ***
## A:B:E       1   44.96   44.96 27.635 3.82e-05 ***
## A:D:E       1   26.01   26.01 15.988 0.000706 ***
## Residuals   20   32.54   1.63
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

#From the full normal plot, it shows that factors A,D,E,A:D,D:E,B:E,A:B,A:E,A:B:E,A:D:E are significant.
#Also ANOVA analysis shows the factors A D E AB AD AE BE DE ABE ADE as significant.

#(b) One of the factors from this experiment does not seem to be important. If you drop this factor, what type of design remains? Analyze the data using the full factorial model for only the four active factors, including model adequacy checking.

```
Model2 <- lm(Obs~A*B*D*E,data = Data)  
coef(Model2)
```

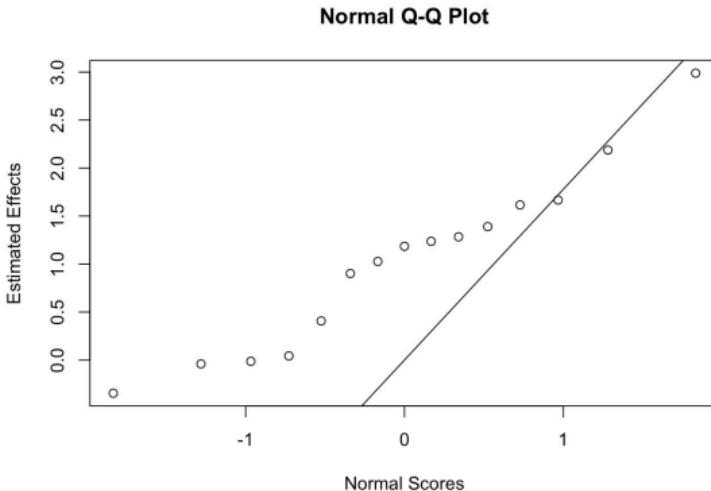
```

## (Intercept)      A      B      C      D      E
## 10.1803125  1.6159375  0.0434375 -0.0121875  2.9884375  2.1878125
##          A:B     A:C     B:C     A:D     B:D     C:D
## 1.2365625 -0.0015625 -0.1953125  1.6665625 -0.0134375  0.0034375
##          A:E     B:E     C:E     D:E     A:B:C     A:B:D
## 1.0271875  1.2834375  0.3015625  1.3896875  0.2503125 -0.3453125
##          A:D     B:D     C:D     D:D     A:B:D     A:C:D

```

```
##          A:C:D      B:C:D      A:B:E      A:C:E      B:C:E      A:D:E
## -0.0634375  0.3053125  1.1853125 -0.2590625  0.1709375  0.9015625
##          B:D:E      C:D:E      A:B:C:D    A:B:C:E    A:B:D:E    A:C:D:E
## -0.0396875  0.3959375 -0.0740625 -0.1846875  0.4071875  0.1278125
##          B:C:D:E   A:B:C:D:E
## -0.0746875 -0.3553125
```

```
fullnormal(coef(Model2)[-1],alpha=.025)
```



```
summary(Model2)
```

```
##
## Call:
## lm(formula = Obs ~ A * B * D * E, data = Data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.4750 -0.5637  0.0000  0.5637  1.4750
##
```



```

## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.18031   0.21360 47.661 < 2e-16 ***
## A            1.61594   0.21360  7.565 1.14e-06 ***
## B            0.04344   0.21360  0.203 0.841418
## D            2.98844   0.21360 13.991 2.16e-10 ***
## E            2.18781   0.21360 10.243 1.97e-08 ***
## A:B          1.23656   0.21360  5.789 2.77e-05 ***
## A:D          1.66656   0.21360  7.802 7.66e-07 ***
## B:D          -0.01344   0.21360 -0.063 0.950618
## A:E          1.02719   0.21360  4.809 0.000193 ***
## B:E          1.28344   0.21360  6.009 1.82e-05 ***
## D:E          1.38969   0.21360  6.506 7.24e-06 ***
## A:B:D        -0.34531   0.21360 -1.617 0.125501
## A:B:E        1.18531   0.21360  5.549 4.40e-05 ***
## A:D:E        0.90156   0.21360  4.221 0.000650 ***
## B:D:E        -0.03969   0.21360 -0.186 0.854935
## A:B:D:E     0.40719   0.21360  1.906 0.074735 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.208 on 16 degrees of freedom
## Multiple R-squared:  0.9744, Adjusted R-squared:  0.9504
## F-statistic: 40.58 on 15 and 16 DF, p-value: 7.07e-10

```

```

Model3 <- aov(Obs~A+B+D+E+A*B+A*D+A*E+B*E+D*E+A*B*E+A*D*E,data = Data)
summary(Model3)

```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)						
## A	1	83.56	83.56	51.362	6.10e-07 ***						
## B	1	0.06	0.06	0.037	0.849178						
## D	1	285.78	285.78	175.664	2.30e-11 ***						
## E	1	153.17	153.17	94.149	5.24e-09 ***						
## A:B	1	48.93	48.93	30.076	2.28e-05 ***						
## A:D	1	88.88	88.88	54.631	3.87e-07 ***						
## A:E	1	33.76	33.76	20.754	0.000192 ***						
## B:E	1	52.71	52.71	32.400	1.43e-05 ***						
## D:E	1	61.80	61.80	37.986	5.07e-06 ***						
## A:B:E	1	44.96	44.96	27.635	3.82e-05 ***						
## A:D:E	1	26.01	26.01	15.988	0.000706 ***						
## Residuals	20	32.54	1.63								
## ---											
## Signif. codes:	0	'***'	0.001	'**'	0.01	'*'	0.05	.	0.1	' '	1

#From (a), the factor c seems to be not important, also there are no interactions which are significant with c. S



```
#From (a), the factor c seems to be not important, also there are no interactions which are significant with c, S  
o, I dropped the  
#factor c. This is 2^4 factorial design.  
#Even though I drop the factor c, the remaining 4 factors still  
#have the same results as the (a).  
  
#For the model checking,
```

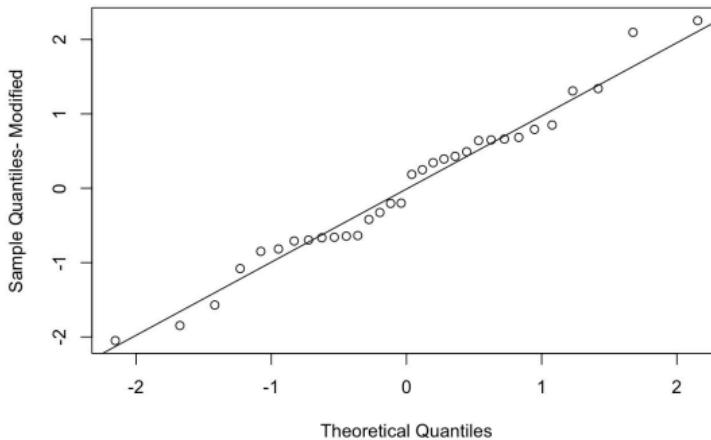
```
#model checking  
#Final model - remove non-significant terms  
res.aov<-aov(Model3)  
summary(res.aov)
```

```
##          Df Sum Sq Mean Sq F value    Pr(>F)  
## A          1   83.56   83.56  51.362 6.10e-07 ***  
## B          1    0.06    0.06   0.037  0.849178  
## D          1 285.78  285.78 175.664 2.30e-11 ***  
## E          1 153.17  153.17  94.149 5.24e-09 ***  
## A:B         1   48.93   48.93  30.076 2.28e-05 ***  
## A:D         1   88.88   88.88  54.631 3.87e-07 ***  
## A:E         1   33.76   33.76  20.754 0.000192 ***  
## B:E         1   52.71   52.71  32.400 1.43e-05 ***  
## D:E         1   61.80   61.80  37.986 5.07e-06 ***  
## A:B:E       1   44.96   44.96  27.635 3.82e-05 ***  
## A:D:E       1   26.01   26.01  15.988 0.000706 ***  
## Residuals   20   32.54    1.63  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#Residual Analysis  
#Normality  
engineer_residuals=res.aov$residuals  
qqnorm(engineer_residuals, ylim=c(min(engineer_residuals),max(engineer_residuals)), main = "Normal Q-Q Plot for R  
esiduals",  
      xlab = "Theoretical Quantiles", ylab = "Sample Quantiles- Modified",  
      plot.it = TRUE, datax = FALSE)  
  
qqline(engineer_residuals, datax = FALSE, distribution = qnorm)
```

Normal Q-Q Plot for Residuals

Normal Q-Q Plot for Residuals

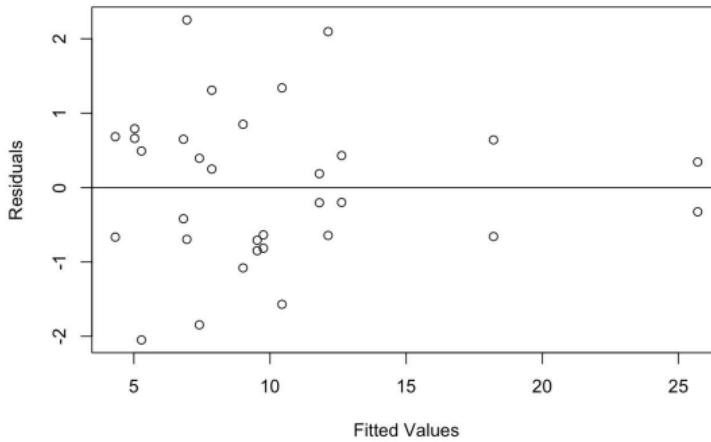


```
#Test normality using Shapiro Wilks
shapiro.test(engineer_residuals)
```

```
## 
## Shapiro-Wilk normality test
##
## data: engineer_residuals
## W = 0.97507, p-value = 0.6491
```

```
#Check Variance
Fitted_values=res.aov$fitted.values
plot(Fitted_values,engineer_residuals,ylab="Residuals",xlab="Fitted Values")
abline(h=0)
```





```
#From the q-q plot for residuals, the almost of all data are near the straight line. Also, by the Shapiro-Wilk test, Since the p-value(0.6491) is greater than 0.05, we fail to reject the null hypothesis that the data is normally distributed.
```

```
#it means the distribution is normally distributed.
```

```
#Moreover, The residual vs fitted value plot shows  
# that the pattern of scatter is the almost same.  
#so the variance is adequate  
#So this is an adequate model to test.
```

```
##(c)Find settings of the active factors that maximize the predicted response.
```

```
#Based on the transformed data above we got  
# $Y_{i,j,k,l} = 10.1803125 + 1.6159375\alpha_i + 0.0434375\beta_j + 2.9884375\gamma_k$   
#+ 2.1878125\delta_l + \epsilon_{i,j,k,l}
```

###Question5

```
#Consider the full 25 factorial design Question 4 above. Suppose that  
#this experiment had been run in two blocks with ABCDE confounded with the  
#blocks. Set up the blocked design and perform the analysis. Compare your results  
#with the results obtained for the completely randomized design in Question 4.
```

```
##G = S'(1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1)
```

```
A <- c(-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1)
B <- c(-1,-1,1,1,-1,-1,1,1,-1,-1,1,1,-1,-1,1,1,-1,-1,1,1,-1,1,1,-1,1,1)
C <- c(-1,-1,-1,-1,1,1,-1,-1,-1,1,1,1,-1,-1,1,1,1,-1,-1,-1,1,1,1,1)
D <- c(-1,-1,-1,-1,-1,-1,1,1,1,1,1,1,-1,-1,-1,-1,-1,-1,1,1,1,1,1,1)
E <- c(-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,1,1,1,1,1,1)
Obs <- c(8.11,5.56,5.77,5.82,9.17,7.8,3.23,5.69,8.82,14.23,9.2,8.94,8.68,11.49,6.25,9.12,7.93,5,7.47,12,9.86,3.6
5,6.4,11.61,12.43,17.55,8.87,25.38,13.06,18.85,11.78,26.05)
# Define the block variable
#positive is 2 negative 1 is 1
block <- c(1,2,2,1,2,1,1,2,2,1,1,2,2,2,1,2,1,1,2,2,1,1,2,2,1,1,2,1,1,2)

Data <- data.frame(A,B,C,D,E,Obs,block)
```

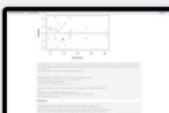
```
# Fit the model with the block effect and confounding ABCDE with blocks
Model_Mod <- lm(Obs ~ block + A*B*C*D*E, data = Data)
```

```
# Display the ANOVA table for the modified design
anova_table_Mod <- anova(Model_Mod)
```

```
## Warning in anova.lm(Model_Mod): ANOVA F-tests on an essentially perfect fit are
## unreliable
```

```
print(anova_table_Mod)
```

```
## Analysis of Variance Table
##
## Response: Obs
##             Df  Sum Sq Mean Sq F value Pr(>F)
## block        1   4.040   4.040   NaN    NaN
## A            1  83.560  83.560   NaN    NaN
## B            1   0.060   0.060   NaN    NaN
## C            1   0.005   0.005   NaN    NaN
## D            1 285.784 285.784   NaN    NaN
## E            1 153.169 153.169   NaN    NaN
## A:B          1  48.931  48.931   NaN    NaN
## A:C          1   0.000   0.000   NaN    NaN
## B:C          1   1.221   1.221   NaN    NaN
## A:D          1  88.878  88.878   NaN    NaN
## B:D          1   0.006   0.006   NaN    NaN
## C:D          1   0.000   0.000   NaN    NaN
## A:E          1  33.764  33.764   NaN    NaN
## B:E          1  52.711  52.711   NaN    NaN
## C:E          1   2.910   2.910   NaN    NaN
## D:E          1  61.799  61.799   NaN    NaN
```



```
## C:D      1   0.000   0.000   NaN   NaN
## A:E      1   33.764  33.764   NaN   NaN
## B:E      1   52.711  52.711   NaN   NaN
## C:E      1   2.910   2.910   NaN   NaN
## D:E      1   61.799  61.799   NaN   NaN
## A:B:C    1   2.005   2.005   NaN   NaN
## A:B:D    1   3.816   3.816   NaN   NaN
## A:C:D    1   0.129   0.129   NaN   NaN
## B:C:D    1   2.983   2.983   NaN   NaN
## A:B:E    1   44.959  44.959   NaN   NaN
## A:C:E    1   2.148   2.148   NaN   NaN
## B:C:E    1   0.935   0.935   NaN   NaN
## A:D:E    1   26.010  26.010   NaN   NaN
## B:D:E    1   0.050   0.050   NaN   NaN
## C:D:E    1   5.017   5.017   NaN   NaN
## A:B:C:D  1   0.176   0.176   NaN   NaN
## A:B:C:E  1   1.092   1.092   NaN   NaN
## A:B:D:E  1   5.306   5.306   NaN   NaN
## A:C:D:E  1   0.523   0.523   NaN   NaN
## B:C:D:E  1   0.179   0.179   NaN   NaN
## Residuals 0   0.000   NaN
```

```
#This is from question4
A <- c(-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1,-1,1)
B <- c(-1,-1,1,1,-1,-1,1,1,-1,-1,1,1,-1,-1,1,1,-1,-1,1,1,-1,-1,1,1)
C <- c(-1,-1,-1,1,1,1,-1,-1,-1,1,1,1,1,-1,-1,-1,1,1,1,1,-1,-1,-1,1,1,1)
D <- c(-1,-1,-1,-1,-1,-1,1,1,1,1,1,1,-1,-1,-1,-1,-1,-1,-1,1,1,1,1)
E <- c(-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,1,1,1,1,1,1,1,1)
Obs <- c(8.11,5.56,5.77,5.82,9.17,7.8,3.23,5.69,8.82,14.23,9.2,8.94,8.68,11.49,6.25,9.12,7.93,5.747,12.9.86,3.6
5.6.4,11.61,12.43,17.55,8.87,25.38,13.06,18.85,11.78,26.05)
Data <- data.frame(A,B,C,D,E,Obs)
Data
```

```
##   A   B   C   D   E   Obs
## 1 -1 -1 -1 -1 -1  8.11
## 2  1 -1 -1 -1 -1  5.56
## 3 -1  1 -1 -1 -1  5.77
## 4  1  1 -1 -1 -1  5.82
## 5 -1 -1  1 -1 -1  9.17
## 6  1 -1  1 -1 -1  7.80
## 7 -1  1  1 -1 -1  3.23
## 8  1  1  1 -1 -1  5.69
## 9 -1 -1 -1  1 -1  8.82
## 10 1 -1 -1  1 -1 14.23
## 11 -1  1 -1  1 -1  9.20
## 12 1  1 -1  1 -1  8.94
```



```
## 13 -1 -1 1 1 -1 8.68
## 14 1 -1 1 1 -1 11.49
## 15 -1 1 1 1 -1 6.25
## 16 1 1 1 1 -1 9.12
## 17 -1 -1 -1 -1 1 7.93
## 18 1 -1 -1 -1 1 5.00
## 19 -1 1 -1 -1 1 7.47
## 20 1 1 -1 -1 1 12.00
## 21 -1 -1 1 -1 1 9.86
## 22 1 -1 1 -1 1 3.65
## 23 -1 1 1 -1 1 6.40
## 24 1 1 1 -1 1 11.61
## 25 -1 -1 -1 1 1 12.43
## 26 1 -1 -1 1 1 17.55
## 27 -1 1 -1 1 1 8.87
## 28 1 1 -1 1 1 25.38
## 29 -1 -1 1 1 1 13.06
## 30 1 -1 1 1 1 18.85
## 31 -1 1 1 1 1 11.78
## 32 1 1 1 1 1 26.05
```

```
Model <- lm(Obs~A*B*C*D*E,data = Data)
aov.model = aov(Model)
summary(aov.model)
```

	Df	Sum Sq	Mean Sq
## A	1	83.56	83.56
## B	1	0.06	0.06
## C	1	0.00	0.00
## D	1	285.78	285.78
## E	1	153.17	153.17
## A:B	1	48.93	48.93
## A:C	1	0.00	0.00
## B:C	1	1.22	1.22
## A:D	1	88.88	88.88
## B:D	1	0.01	0.01
## C:D	1	0.00	0.00
## A:E	1	33.76	33.76
## B:E	1	52.71	52.71
## C:E	1	2.91	2.91
## D:E	1	61.80	61.80
## A:B:C	1	2.01	2.01
## A:B:D	1	3.82	3.82
## A:C:D	1	0.13	0.13
## B:C:D	1	2.98	2.98
## A:B:E	1	44.96	44.96



```
## 29 -1 -1 1 1 1 13.06
## 30 1 -1 1 1 1 18.85
## 31 -1 1 1 1 1 11.78
## 32 1 1 1 1 1 26.05
```

```
Model <- lm(Obs~A*B*C*D*E,data = Data)
aov.model = aov(Model)
summary(aov.model)
```

	Df	Sum Sq	Mean Sq
## A	1	83.56	83.56
## B	1	0.06	0.06
## C	1	0.00	0.00
## D	1	285.78	285.78
## E	1	153.17	153.17
## A:B	1	48.93	48.93
## A:C	1	0.00	0.00
## B:C	1	1.22	1.22
## A:D	1	88.88	88.88
## B:D	1	0.01	0.01
## C:D	1	0.00	0.00
## A:E	1	33.76	33.76
## B:E	1	52.71	52.71
## C:E	1	2.91	2.91
## D:E	1	61.80	61.80
## A:B:C	1	2.01	2.01
## A:B:D	1	3.82	3.82
## A:C:D	1	0.13	0.13
## B:C:D	1	2.98	2.98
## A:B:E	1	44.96	44.96
## A:C:E	1	2.15	2.15
## B:C:E	1	0.94	0.94
## A:D:E	1	26.01	26.01
## B:D:E	1	0.05	0.05
## C:D:E	1	5.02	5.02
## A:B:C:D	1	0.18	0.18
## A:B:C:E	1	1.09	1.09
## A:B:D:E	1	5.31	5.31
## A:C:D:E	1	0.52	0.52
## B:C:D:E	1	0.18	0.18
## A:B:C:D:E	1	4.04	4.04

#Compared to the design from question 4, the value of question 5 has less values.