Assignment#

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Question 1

```r
# Clear the environment
rm(list = ls())

require("conf.design")
```

```
## Loading required package: conf.design
```

```r
# Define the factors and response variable
A = rep(c(-1, 1), 8)
B = rep(c(rep(-1, 2), rep(1, 2)), 4)
C = rep(c(rep(-1, 4), rep(1, 4)), 2)
D = c(rep(-1, 8), rep(1, 8))
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)

# Create a data frame
credit_card_data <- data.frame(y, A, B, C, D)

# Fit a linear model
res.lm <- lm(y ~ A * B * C * D, data = credit_card_data)

# Summary of the linear model to check p-values
summary_res_lm <- summary(res.lm)

# Print the summary
print(summary_res_lm)
```

```
##
## Call:
## lm(formula = y ~ A * B * C * D, data = credit_card_data)
##
## Residuals:
## ALL 16 residuals are 0: no residual degrees of freedom!
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.36375        NaN     NaN      NaN
## A            0.20375        NaN     NaN      NaN
## B           -0.25875        NaN     NaN      NaN
## C            0.12625        NaN     NaN      NaN
## D           -0.24875        NaN     NaN      NaN
```

```
## A:B         -0.15125        NaN     NaN      NaN
## A:C          0.00125        NaN     NaN      NaN
## B:C         -0.02375        NaN     NaN      NaN
## A:D         -0.05375        NaN     NaN      NaN
## B:D          0.05125        NaN     NaN      NaN
## C:D          0.07875        NaN     NaN      NaN
## A:B:C       -0.02625        NaN     NaN      NaN
## A:B:D        0.04375        NaN     NaN      NaN
## A:C:D        0.00375        NaN     NaN      NaN
## B:C:D       -0.05375        NaN     NaN      NaN
## A:B:C:D     -0.02625        NaN     NaN      NaN
##
## Residual standard error: NaN on 0 degrees of freedom
## Multiple R-squared:      1,  Adjusted R-squared:    NaN
## F-statistic:   NaN on 15 and 0 DF,  p-value: NA
```

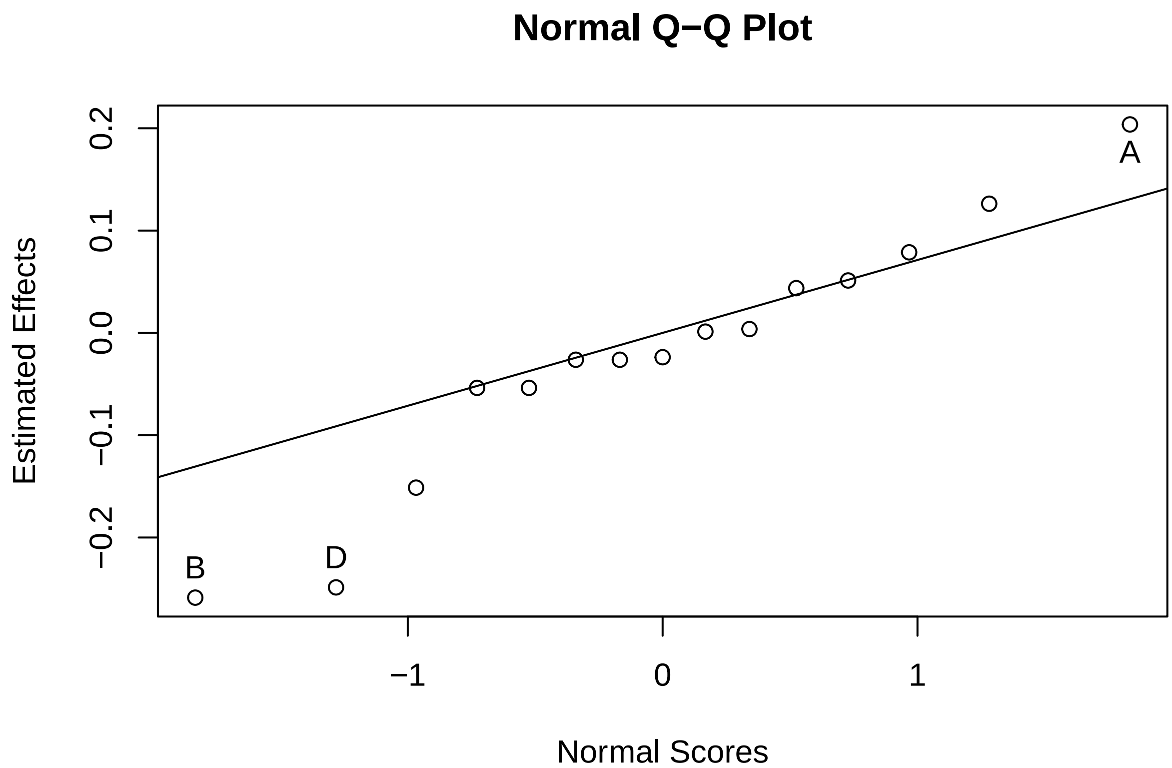
```r
# Alternatively, you can use ANOVA
res.aov <- aov(y ~ A * B * C * D, data = credit_card_data)
summary_res_aov <- summary(res.aov)

# Print the ANOVA summary
print(summary_res_aov)
```

```
##             Df Sum Sq Mean Sq
## A            1 0.6642  0.6642
## B            1 1.0712  1.0712
## C            1 0.2550  0.2550
## D            1 0.9900  0.9900
## A:B          1 0.3660  0.3660
## A:C          1 0.0000  0.0000
## B:C          1 0.0090  0.0090
## A:D          1 0.0462  0.0462
## B:D          1 0.0420  0.0420
## C:D          1 0.0992  0.0992
## A:B:C        1 0.0110  0.0110
## A:B:D        1 0.0306  0.0306
## A:C:D        1 0.0002  0.0002
## B:C:D        1 0.0462  0.0462
## A:B:C:D      1 0.0110  0.0110
```

```r
library(daewr)
```

```
## Warning: package 'daewr' was built under R version 4.2.3
```

```r
fullnormal(coef(res.lm)[-1],alpha=.05)
```



Part a

From the plot, we can conclude that factor C(Initial interest rate) are not significant.

Part b

```
credit_card_data_Reduced <- within(credit_card_data, rm(C))

# Fit an ANOVA model to the reduced dataset
res.aov_reduced <- aov(y~A*B*D, data=credit_card_data_Reduced)
summary(res.aov_reduced)
```

```
##             Df Sum Sq Mean Sq F value  Pr(>F)
## A            1 0.6642  0.6642  12.306 0.00798 **
## B            1 1.0712  1.0712  19.847 0.00213 **
## D            1 0.9900  0.9900  18.342 0.00268 **
## A:B          1 0.3660  0.3660   6.781 0.03142 *
## A:D          1 0.0462  0.0462   0.856 0.38181
## B:D          1 0.0420  0.0420   0.779 0.40330
## A:B:D        1 0.0306  0.0306   0.567 0.47288
## Residuals    8 0.4318  0.0540
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Fit a linear model to the reduced dataset
res.lm_reduced <- lm(y~A*B*D, data=credit_card_data_Reduced)
```

```r
summary(res.lm_reduced)
```

```
##
## Call:
## lm(formula = y ~ A * B * D, data = credit_card_data_Reduced)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -0.34  -0.08   0.00   0.08   0.34
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.36375    0.05808  40.697 1.46e-10 ***
## 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 **
## 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        0.04375    0.05808   0.753  0.47288
## ---
## 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
```

Part c

The coefficient for B in the model output is -0.25875. This is the estimate of the main effect of the account-opening fee on the response rate. It means that, all else being equal, introducing an account-opening fee is associated with a decrease in the response rate by 0.25875 units on the scale of the response variable being measured.

part D

According to the ANOVA summary and the regression output, the account-opening fee (factor B) is significant. The p-value for factor B is 0.00213, which is less than 0.05 , which means there is a statistically significant association between the account-opening fee and the response rate. The "Estimate" value of -0.25875 for B and its corresponding low p-value suggest that the account-opening fee has a significant negative effect on the response rate.

part e

```
## Block 1 Block 2
##  2.4075  2.3200
```

Question 2

Part a

```r
treatments <- c("1", "a", "b", "ab", "c", "ac", "bc", "abc", "d", "ad", "bd", "abd", "cd", "acd", "bcd"
replicate1 <- c(90, 74, 81, 83, 77, 81, 88, 73, 98, 72, 87, 85, 99, 79, 87, 80)
```

```r
replicate2 <- c(93, 78, 85, 80, 78, 80, 82, 70, 95, 76, 83, 86, 90, 75, 84, 80)
# Calculating average yields
average_yields <- (replicate1 + replicate2) / 2
n <- length(treatments)

# Main effects
effect_A <- (sum(average_yields[c(2,4,6,8,10,12,14,16)]) - sum(average_yields[c(1,3,5,7,9,11,13,15)])) /
effect_B <- (sum(average_yields[c(3,4,7,8,11,12,15,16)]) - sum(average_yields[c(1,2,5,6,9,10,13,14)])) /
effect_C <- (sum(average_yields[c(5,6,7,8,13,14,15,16)]) - sum(average_yields[c(1,2,3,4,9,10,11,12)])) /
effect_D <- (sum(average_yields[c(9,10,11,12,13,14,15,16)]) - sum(average_yields[c(1,2,3,4,5,6,7,8)])) /


# Output main effects
list(A = effect_A, B = effect_B, C = effect_C, D = effect_D)
```

```
## $A
## [1] -9.0625
##
## $B
## [1] -1.3125
##
## $C
## [1] -2.6875
##
## $D
## [1] 3.9375
```

part b

```r
# Define the treatment combinations
coded_combinations <- expand.grid(A = c(-1, 1), B = c(-1, 1), C = c(-1, 1), D = c(-1, 1))
coded_combinations$Yield <- average_yields

# Check the data frame
print(coded_combinations)
```

```
##     A  B  C  D Yield
## 1  -1 -1 -1 -1  91.5
## 2   1 -1 -1 -1  76.0
## 3  -1  1 -1 -1  83.0
## 4   1  1 -1 -1  81.5
## 5  -1 -1  1 -1  77.5
## 6   1 -1  1 -1  80.5
## 7  -1  1  1 -1  85.0
## 8   1  1  1 -1  71.5
## 9  -1 -1 -1  1  96.5
## 10  1 -1 -1  1  74.0
## 11 -1  1 -1  1  85.0
## 12  1  1 -1  1  85.5
## 13 -1 -1  1  1  94.5
## 14  1 -1  1  1  77.0
## 15 -1  1  1  1  85.5
## 16  1  1  1  1  80.0
```

```r
# Create a linear model with all interactions
model <- lm(Yield ~ A*B*C*D, data = coded_combinations)
# Summary of the model to see coefficients and statistics
summary(model)
```

```
##
## Call:
## lm(formula = Yield ~ A * B * C * D, data = coded_combinations)
##
## Residuals:
## ALL 16 residuals are 0: no residual degrees of freedom!
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 82.78125        NaN     NaN      NaN
## A           -4.53125        NaN     NaN      NaN
## B           -0.65625        NaN     NaN      NaN
## C           -1.34375        NaN     NaN      NaN
## D            1.96875        NaN     NaN      NaN
## A:B          2.03125        NaN     NaN      NaN
## A:C          0.34375        NaN     NaN      NaN
## B:C         -0.28125        NaN     NaN      NaN
## A:D         -1.09375        NaN     NaN      NaN
## B:D         -0.09375        NaN     NaN      NaN
## C:D          0.84375        NaN     NaN      NaN
## A:B:C       -2.59375        NaN     NaN      NaN
## A:B:D        2.34375        NaN     NaN      NaN
## A:C:D       -0.46875        NaN     NaN      NaN
## B:C:D       -0.46875        NaN     NaN      NaN
## A:B:C:D      1.21875        NaN     NaN      NaN
##
## Residual standard error: NaN on 0 degrees of freedom
## Multiple R-squared:      1,  Adjusted R-squared:    NaN
## F-statistic:   NaN on 15 and 0 DF,  p-value: NA
```

```r
# Perform ANOVA analysis
anova_result <- anova(model)
```

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

```r
# Print the ANOVA table
print(anova_result)
```

```
## Analysis of Variance Table
##
## Response: Yield
##           Df Sum Sq Mean Sq F value Pr(>F)
## A          1 328.52  328.52     NaN    NaN
## B          1   6.89    6.89     NaN    NaN
## C          1  28.89   28.89     NaN    NaN
## D          1  62.02   62.02     NaN    NaN
## A:B        1  66.02   66.02     NaN    NaN
## A:C        1   1.89    1.89     NaN    NaN
## B:C        1   1.27    1.27     NaN    NaN
```

```
## A:D        1  19.14   19.14     NaN    NaN
## B:D        1   0.14    0.14     NaN    NaN
## C:D        1  11.39   11.39     NaN    NaN
## A:B:C      1 107.64  107.64     NaN    NaN
## A:B:D      1  87.89   87.89     NaN    NaN
## A:C:D      1   3.52    3.52     NaN    NaN
## B:C:D      1   3.52    3.52     NaN    NaN
## A:B:C:D    1  23.77   23.77     NaN    NaN
## Residuals  0   0.00     NaN
```

Part C

Yield=82.78125-4.53125A-0.65625B-1.34375C+1.96875D+2.03125(AB)+0.34375(AC)-0.28125(BC)-1.09375(AD)-0.09375(BD)+0.84375(CD)-2.59375(ABC)+2.34375(ABD)-0.46875(ACD)-0.46875(BCD)+1.21875(ABCD)

Part D

NO, indicated by zero residuals for all observations, suggests an overfitting scenario rather than a meaningful assessment of model adequacy.

Question3

Part a

B(-8.2045), C(-6.5304), D(-6.0275) The larger estimates would be more significant.

part b

This would mean that the combined effect of factors A and B is highly significant and should be a primary focus in understanding the system's behavior or in optimizing the response variable.

Question 4

```r
A = rep(c(-1, 1), times = 16)
B = rep(c(rep(-1, 2), rep(1, 2)), times = 8)
C = rep(c(rep(-1, 4), rep(1, 4)), times = 4)
D = rep(c(rep(-1, 8), rep(1, 8)), times = 2)
E = rep(c(-1, 1), each = 16)
y = 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, 3.65, 6.4, 11.61,
      12.43, 17.55, 8.87, 25.38, 13.06, 18.85, 11.78, 26.05)
# Create the data frame
experiment_data <- data.frame(A, B, C, D, E, y)
full_model <- lm(y ~ A*B*C*D*E, data = experiment_data)


# Summary of the full model to see coefficients
summary(full_model)
```

```
##
## Call:
## lm(formula = y ~ A * B * C * D * E, data = experiment_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
```

```r
# Perform ANOVA analysis
anova_full_model <- anova(full_model)
```

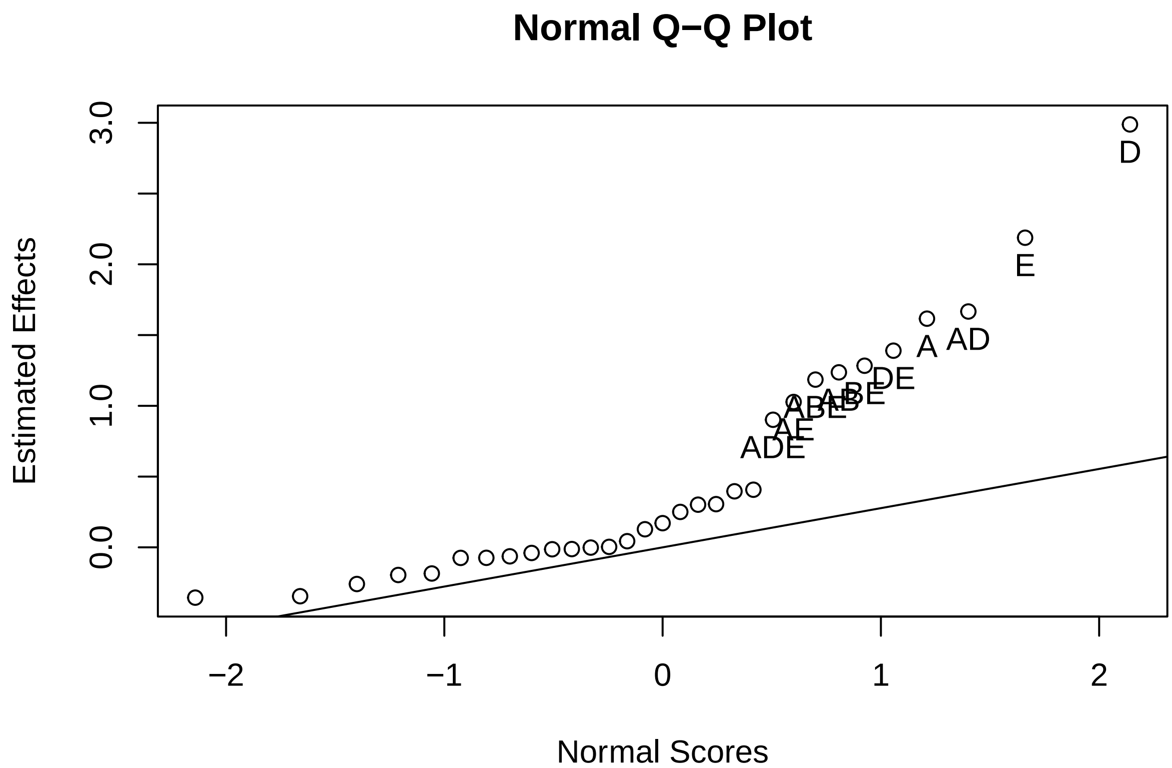
```
## Warning in anova.lm(full_model): ANOVA F-tests on an essentially perfect fit
## are unreliable
```

```r
# Print the ANOVA table
print(anova_full_model)
```

```
## Analysis of Variance Table
##
## Response: y
##             Df  Sum Sq Mean Sq F value Pr(>F)
## 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
## 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
## A:B:C:D:E   1   4.040   4.040     NaN    NaN
## Residuals   0   0.000     NaN
```

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



Througth the plot , the factor C seems to be non-significant terms, so we remove C.

Part b

```
partB_model <- lm(y ~ A*B*D*E, data = experiment_data)
summary(partB_model)
```

```
##
## Call:
## lm(formula = y ~ A * B * D * E, data = experiment_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 ***
```

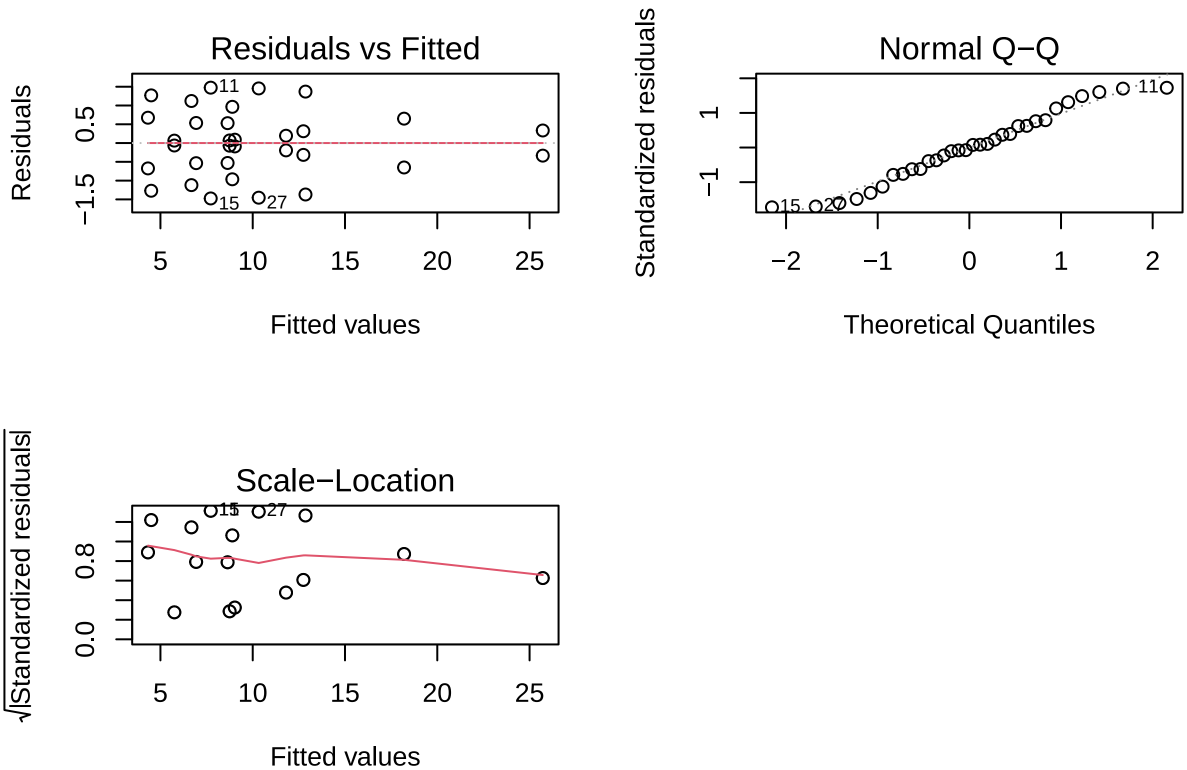
```
## D:E          1.38969    0.21360   6.506 7.24e-06 ***
## A:B:D       -0.34531    0.21360  -1.617 0.125501
## A:B:E        1.18531    0.21360   5.549 4.40e-05 ***
## A:D:E        0.90156    0.21360   4.221 0.000650 ***
## B:D:E       -0.03969    0.21360  -0.186 0.854935
## A:B:D:E      0.40719    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
```

```
anova_partB_model <- anova(partB_model)
print(anova_partB_model)
```

```
## Analysis of Variance Table
##
## Response: y
##           Df  Sum Sq Mean Sq  F value    Pr(>F)
## A          1  83.560  83.560  57.2328 1.136e-06 ***
## B          1   0.060   0.060   0.0414 0.8414184
## D          1 285.784 285.784 195.7422 2.161e-10 ***
## E          1 153.169 153.169 104.9099 1.966e-08 ***
## A:B        1  48.931  48.931  33.5142 2.767e-05 ***
## A:D        1  88.878  88.878  60.8751 7.661e-07 ***
## B:D        1   0.006   0.006   0.0040 0.9506177
## A:E        1  33.764  33.764  23.1257 0.0001928 ***
## B:E        1  52.711  52.711  36.1032 1.822e-05 ***
## D:E        1  61.799  61.799  42.3283 7.243e-06 ***
## A:B:D      1   3.816   3.816   2.6135 0.1255014
## A:B:E      1  44.959  44.959  30.7937 4.402e-05 ***
## A:D:E      1  26.010  26.010  17.8151 0.0006496 ***
## B:D:E      1   0.050   0.050   0.0345 0.8549347
## A:B:D:E    1   5.306   5.306   3.6340 0.0747350 .
## Residuals 16  23.360   1.460
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#model adequacy checking
# Plot to check for normality of residuals
par(mfrow=c(2,2))
plot(partB_model)
```

```
## hat values (leverages) are all = 0.5
##  and there are no factor predictors; no plot no. 5
```



Part C

Factor A: Positive coefficient - High level (+1) Factor B: Not significant, but its interactions are significant Factor D: Positive coefficient - High level (+1) Factor E: Positive coefficient - High level (+1)

Question 5

```r
# Determine the block assignment based on the ABCDE interaction
experiment_data$Block <- with(experiment_data, A * B * C * D * E)
experiment_data$Block <- ifelse(experiment_data$Block == 1, "Block1", "Block2")
blocked_model <- lm(y ~ A*B*C*D*E + Block, data = experiment_data)
# Summary of the blocked model to see coefficients
summary(blocked_model)
```

```
##
## Call:
## lm(formula = y ~ A * B * C * D * E + Block, data = experiment_data)
##
## Residuals:
## ALL 32 residuals are 0: no residual degrees of freedom!
##
## Coefficients: (1 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  9.825000        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
## BlockBlock2   0.710625        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           1.027187        NaN     NaN      NaN
## B:E           1.283437        NaN     NaN      NaN
## C:E           0.301562        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         0.305313        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           NA         NA      NA       NA
##
## 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
```

```r
anova_blocked_model <- anova(blocked_model)
```

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

```r
print(anova_blocked_model)
```

```
## Analysis of Variance Table
##
## Response: y
##           Df  Sum Sq Mean Sq F value Pr(>F)
## 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
## Block      1   4.040   4.040     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
## 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
```

All 32 residuals are 0, which means the model has a perfect fit to the data with no residual variation. This shows that the model is over-parameterized, there are as many parameters being estimated as there are observations. The significance test are not valid in this test.