Valeria Duran

Math 6357

Homework 4

Problem 4.3:

Using R to conduct the randomized block design of the problem:

```
View(ch4_1)
ch4_1 <- ch4_1[,2:4]
ch4_1 <- data.frame(ch4_1)
ch4_1$Chemist <- as.factor(ch4_1$Chemist) #convert chemist and bolt into factors
ch4_1$Bolt <- as.factor(ch4_1$Bolt)
View(ch4_1)
fit <- aov(ch4_1$Strength ~ ch4_1$Chemist + ch4_1$Bolt)

summary(fit)
              Df Sum Sq Mean Sq F value   Pr(>F)
ch4_1$Chemist  3  12.95    4.32   2.376    0.121
ch4_1$Bolt     4 157.00   39.25  21.606 2.06e-05 ***
Residuals     12  21.80    1.82
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

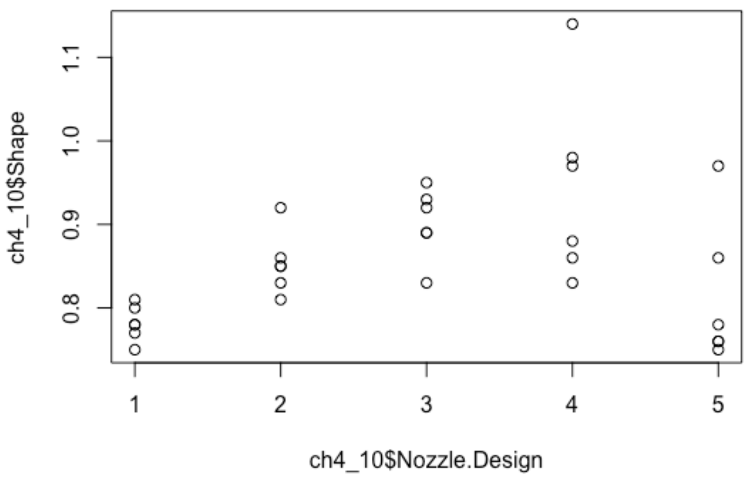
Based off of the ANOVA table, the F value is 2.376. The F critical value is 3.49, therefore, since the F value is less than the F-critical value and the p-value of 0.121 is greater than the significance level of 0.05, we fail to reject the null hypothesis. There is no difference among the chemical types.

Problem 4.10:

Including velocity

a)

```
ch4_10 <- data.frame(ch4_10)
```

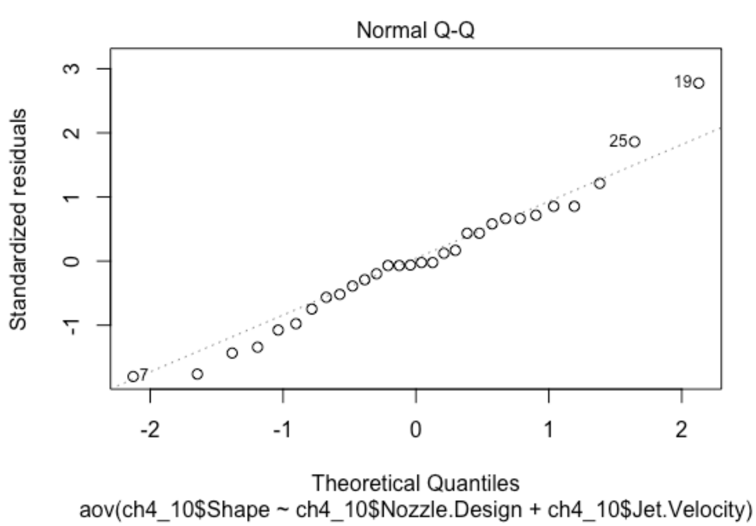


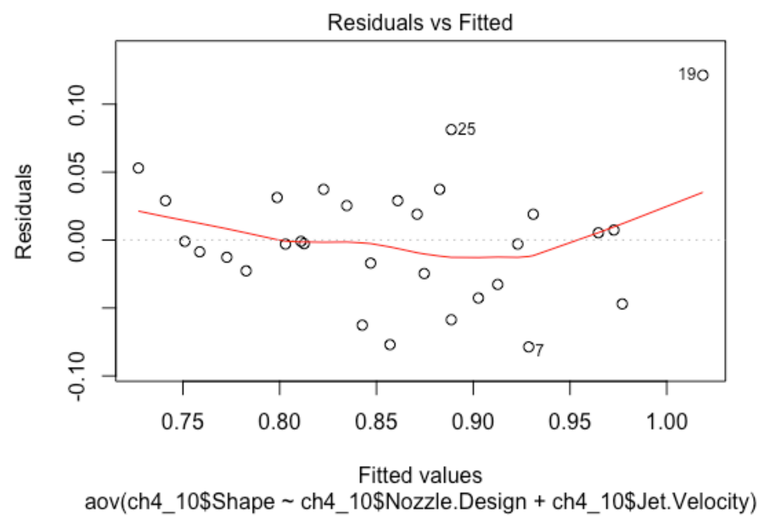

```
ch4_10$Nozzle.Design <- as.factor(ch4_10$Nozzle.Design)
ch4_10$Jet.Velocity <- as.factor(ch4_10$Jet.Velocity)
fit_p10 <- aov(ch4_10$Shape ~ ch4_10$Nozzle.Design + ch4_10$Jet.Velocity)
summary(fit_p10)
                     Df  Sum Sq  Mean Sq F value   Pr(>F)
ch4_10$Nozzle.Design  4 0.10218 0.025545   8.916 0.000266 ***
ch4_10$Jet.Velocity   5 0.06287 0.012573   4.389 0.007364 **
Residuals            20 0.05730 0.002865
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

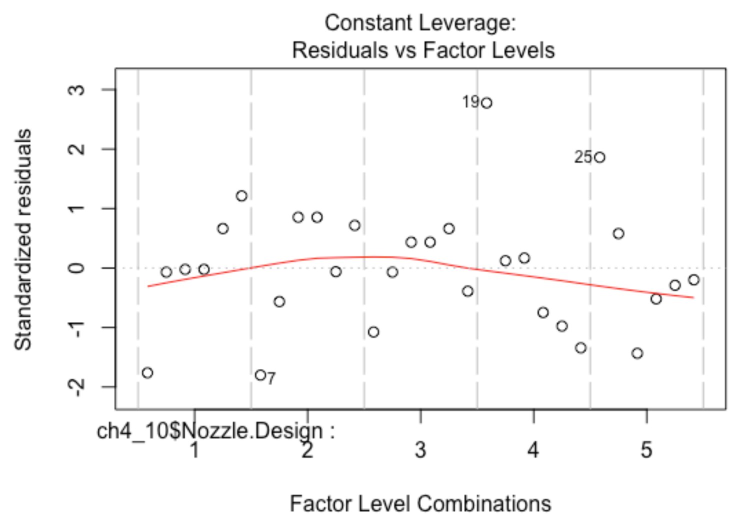
Since the F value of 8.916 is greater than the F critical value of 2.87 and the p-value is less than 0.05, we reject the null hypothesis. The data suggests that nozzle design has a significant effect on shape factor.

b)

```
plot(fit_p10)
```







Based off of the plots, there is not an indication of any issues, although the outliers 7, 19, and 25 may be contributing to the lines not being completely straight.

c)

TukeyHSD(fit_p10, which = "ch4_10$Nozzle.Design")

Tukey multiple comparisons of means

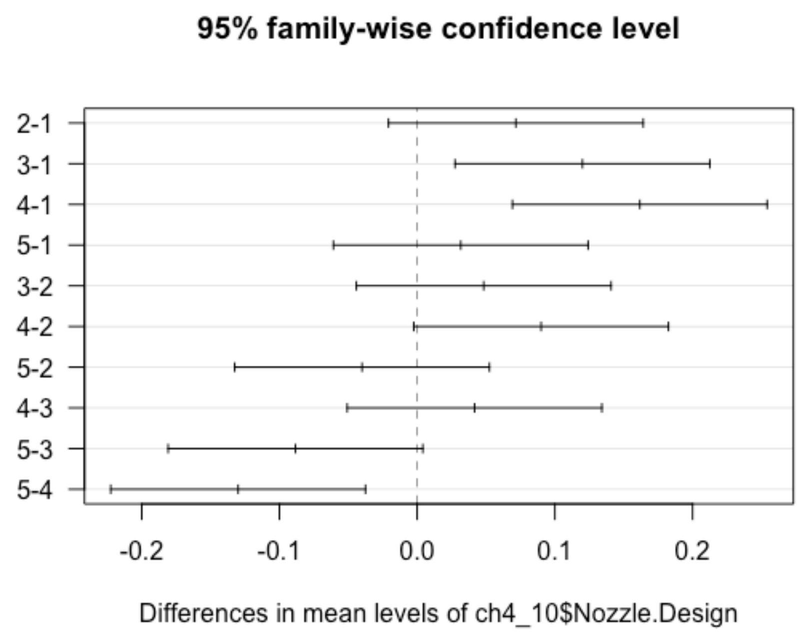
95% family-wise confidence level

Fit: aov(formula = ch4_10$Shape ~ ch4_10$Nozzle.Design + ch4_10$Jet.Velocity)

$`ch4_10$Nozzle.Design`

diff lwr upr p adj

```
2-1  0.07166667 -0.020806907  0.16414024 0.1799301
3-1  0.12000000  0.027526427  0.21247357 0.0073198
4-1  0.16166667  0.069193093  0.25414024 0.0003508
5-1  0.03166667 -0.060806907  0.12414024 0.8410263
3-2  0.04833333 -0.044140240  0.14080691 0.5356545
4-2  0.09000000 -0.002473573  0.18247357 0.0588301
5-2 -0.04000000 -0.132473573  0.05247357 0.6975222
4-3  0.04166667 -0.050806907  0.13414024 0.6656605
5-3 -0.08833333 -0.180806907  0.00414024 0.0655561
5-4 -0.13000000 -0.222473573 -0.03752643 0.0035388
> plot(TukeyHSD(fit_p10, which = "ch4_10$Nozzle.Design"), las = 1)
```



Based off of the plot conducted on the post-hoc test, the nozzle designs that are different with respect to shape factor are: 2 vs 1, 3 vs 1, 4 vs 1, 4 vs 2, 5 vs 3, and 5 vs 4.

```
> duncan.test(fit_p10,"ch4_10$Nozzle.Design",alpha=0.05,console=TRUE)

Study: fit_p10 ~ "ch4_10$Nozzle.Design"
```

Duncan's new multiple range test
for ch4_10$Shape

Mean Square Error: 0.002865

ch4_10$Nozzle.Design, means

	ch4_10.Shape	std	r	Min	Max
1	0.7816667	0.02136976	6	0.75	0.81
2	0.8533333	0.03723797	6	0.81	0.92
3	0.9016667	0.04215052	6	0.83	0.95
4	0.9433333	0.11360751	6	0.83	1.14
5	0.8133333	0.08664102	6	0.75	0.97

Alpha: 0.05 ; DF Error: 20

Critical Range

2	3	4	5
0.06446268	0.06766416	0.06969876	0.07111983

Means with the same letter are not significantly different.

	ch4_10$Shape	groups
4	0.9433333	a
3	0.9016667	ab
2	0.8533333	bc
5	0.8133333	cd
1	0.7816667	d

The Duncan’s multiple range test draws similar conclusions to those based off of the plot.

excluding velocity

```
#without the velocity
fit_p102 <- aov(ch4_10$Shape ~ ch4_10$Nozzle.Design)
> summary(fit_p102)
                      Df Sum Sq  Mean Sq F value  Pr(>F)
ch4_10$Nozzle.Design  4 0.1022 0.025545   5.314 0.00308 **
Residuals            25 0.1202 0.004807
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Nozzle Design becomes less significant (0.003 vs 0.00027) when excluding velocity.

Problem 4.11

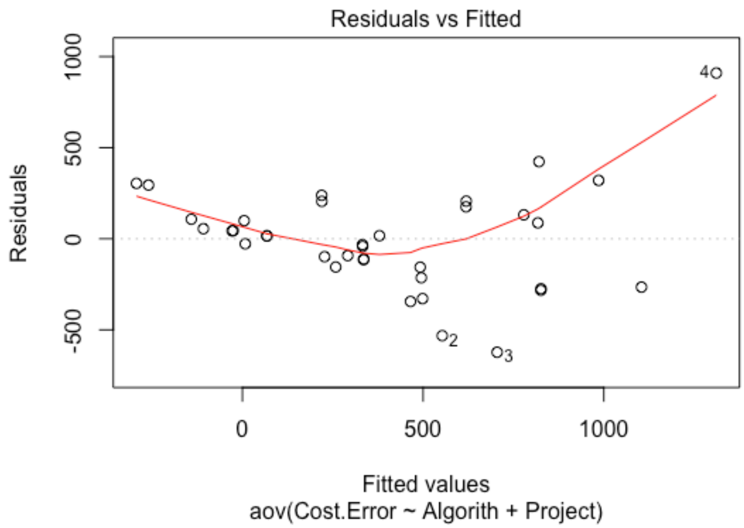
A)

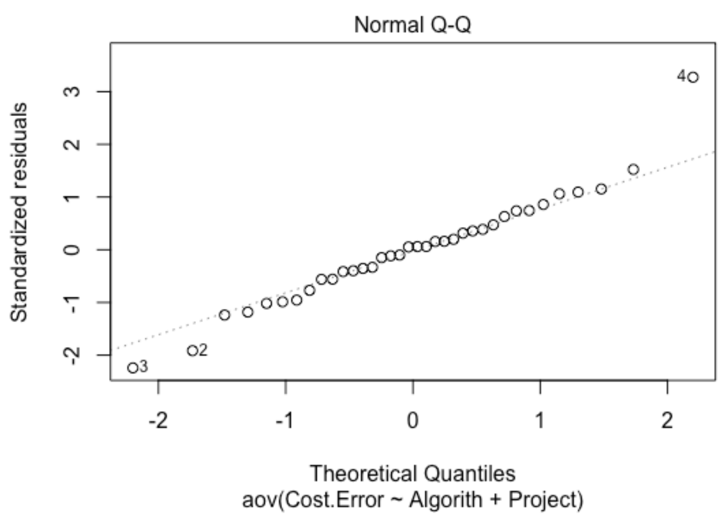
```
ch4_11 <- data.frame(ch4_11)
ch4_11$Project <- as.factor(ch4_11$Project)
ch4_11$Algorith <- as.factor(ch4_11$Algorith)
str(ch4_11)
attach(ch4_11)
fit11 <- aov(Cost.Error ~ Algorith + Project, data = ch4_11)
> summary(fit11)
          Df  Sum Sq Mean Sq F value  Pr(>F)
Algorith     5 2989130  597826   5.377 0.00172 **
Project      5 2287339  457468   4.115 0.00730 **
Residuals   25 2779574  111183
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Based off of the ANOVA table, there is a difference in means since the F value is 5.377 (greater than the F critical value of 2.602987) and the p-value is less than 0.05.

b)

> plot(fit11)





Although the data seems to have equal variance, there are a few outliers that need to be investigated.

C)

> model.tables(fit11, type="means", se = TRUE)

```
Tables of means
Grand mean

392.8056

 Algorith
Algorith
     COCOMO-A       COCOMO-C       COCOMO-R       ESTIMALS FUNCTION POINTS
        559.7          400.3          399.8          72.5          39.2
          SLM
        885.3

 Project
Project
   1     2     3     4     5     6
328.2  60.5 212.3 818.8 325.2 611.8

Standard errors for differences of means
       Algorith Project
          192.5   192.5
replic.        6       6
```

Function Points has the lowest cost estimation error, so this one would be recommended.

D)

```
ch4_11_rem <- aov(Cost.Error ~ Algorith+Project, data = ch4_11[-c(27,31,33),])
summary(ch4_11_rem)
plot(ch4_11_rem)
> summary(ch4_11_rem)
          Df  Sum Sq Mean Sq F value Pr(>F)
```

```
Algorith     5 2430358  486072   3.883 0.0113 *
Project      5 2270499  454100   3.628 0.0152 *
Residuals   22 2753803  125173

model.tables(ch4_11_rem, type="means", se = TRUE)
Design is unbalanced - use se.contrast() for se's
Tables of means
Grand mean

431.7576

 Algorith
   COCOMO-A COCOMO-C COCOMO-R ESTIMALS FUNCTION POINTS   SLM
      559.7    400.3    399.8      127            53.8 885.3
rep     6.0      6.0      6.0        4             5.0   6.0

 Project
       1     2     3     4     5     6
   369.8 87.93 210.7 846.3 352.6 639.3
rep  5.0  6.00   4.0   6.0   6.0   6.0
```

Removing the negative observations makes the differences in means less significant. By removing the negative observations, there is an unbalanced design since now Estimals only has 4 observations and Function Points only has 5. However, Function Points continues to have the lowest cost estimation error.

Problem 4:

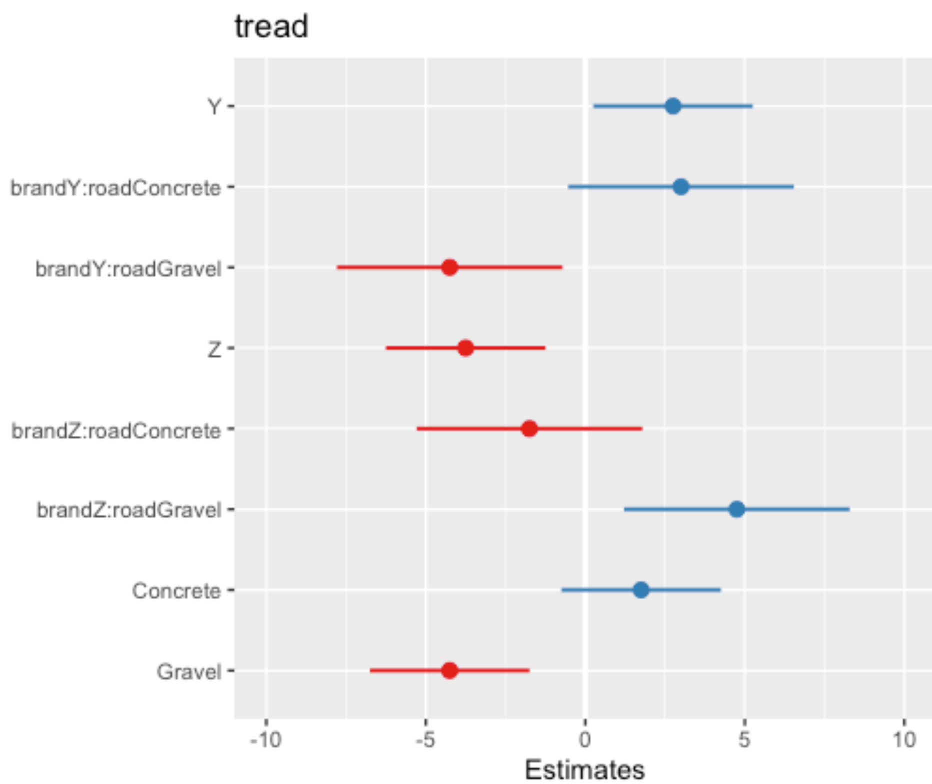
```
> road = as.factor(c(rep("Asphalt", 12), rep("Concrete", 12), rep("Gravel", 12)))
> brand = as.factor(rep(c(rep("X",4), rep("Y",4), rep("Z",4)),3))
> tread = c(36, 39, 39, 38, 42, 40, 39, 42, 32, 36, 35, 34,
```

```
+           38, 40, 41, 40, 42, 45, 48, 47, 37, 33, 33, 34,
+           34, 32, 34, 35, 34, 34, 30, 31, 36, 35, 35, 33)
> tire = data.frame(road, brand, tread)
> ## Brand X and Asphalt as reference level
> fit.tire <- lm(tread ~ brand*road, data = tire)
> summary(fit.tire)

Call:
lm(formula = tread ~ brand * road, data = tire)

Residuals:
   Min     1Q Median     3Q    Max
 -3.50  -1.25   0.25   1.25   2.75

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)           38.000      0.862  44.083  < 2e-16 ***
brandY                 2.750      1.219   2.256  0.03239 *
brandZ                -3.750      1.219  -3.076  0.00476 **
roadConcrete           1.750      1.219   1.436  0.16262
roadGravel            -4.250      1.219  -3.486  0.00169 **
brandY:roadConcrete    3.000      1.724   1.740  0.09323 .
brandZ:roadConcrete   -1.750      1.724  -1.015  0.31908
brandY:roadGravel     -4.250      1.724  -2.465  0.02034 *
brandZ:roadGravel      4.750      1.724   2.755  0.01037 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.724 on 27 degrees of freedom
```

```
Multiple R-squared:  0.8808,  Adjusted R-squared:  0.8454
F-statistic: 24.93 on 8 and 27 DF,  p-value: 1.479e-10
> anova.tire <- aov(fit.tire)
> summary(anova.tire)
            Df Sum Sq Mean Sq F value   Pr(>F)
brand        2 155.39   77.69   26.14 4.84e-07 ***
road         2 241.72  120.86   40.66 7.15e-09 ***
brand:road   4 195.61   48.90   16.45 6.09e-07 ***
Residuals   27  80.25    2.97
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> ## Brand Y and Concrete as reference level
> tire$brand <- relevel(tire$brand, ref = "Y")
> tire$road <- relevel(tire$road, ref = "Concrete")
> fit.tire1 <- lm(tread ~ brand*road, data = tire)
> summary(fit.tire1)

Call:
lm(formula = tread ~ brand * road, data = tire)

Residuals:
   Min     1Q Median     3Q    Max
 -3.50  -1.25   0.25   1.25   2.75

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)         45.500      0.862  52.784  < 2e-16 ***
brandX              -5.750      1.219  -4.717 6.52e-05 ***
brandZ             -11.250      1.219  -9.228 7.72e-10 ***
```

```
roadAsphalt          -4.750      1.219  -3.896 0.000582 ***
roadGravel          -13.250      1.219 -10.869 2.31e-11 ***
brandX:roadAsphalt    3.000      1.724   1.740 0.093225 .
brandZ:roadAsphalt    4.750      1.724   2.755 0.010375 *
brandX:roadGravel     7.250      1.724   4.205 0.000257 ***
brandZ:roadGravel    13.750      1.724   7.976 1.43e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.724 on 27 degrees of freedom
Multiple R-squared:  0.8808,  Adjusted R-squared:  0.8454
F-statistic: 24.93 on 8 and 27 DF,  p-value: 1.479e-10

> anova.tire1 <- aov(fit.tire1)
> summary(anova.tire1)
            Df Sum Sq Mean Sq F value   Pr(>F)
brand        2 155.39   77.69   26.14 4.84e-07 ***
road         2 241.72  120.86   40.66 7.15e-09 ***
brand:road   4 195.61   48.90   16.45 6.09e-07 ***
Residuals   27  80.25    2.97
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> ## Brand Z and Gravel as reference level
> tire$brand <- relevel(tire$brand, ref = "Z")
> tire$road <- relevel(tire$road, ref = "Gravel")
> fit.tire2 <- lm(tread ~ brand*road, data = tire)
> summary(fit.tire2)

Call:
```

```
lm(formula = tread ~ brand * road, data = tire)

Residuals:
   Min     1Q Median     3Q    Max
 -3.50  -1.25   0.25   1.25   2.75

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)         34.750      0.862  40.313  < 2e-16 ***
brandY              -2.500      1.219  -2.051  0.05011 .
brandX              -1.000      1.219  -0.820  0.41923
roadConcrete        -0.500      1.219  -0.410  0.68493
roadAsphalt         -0.500      1.219  -0.410  0.68493
brandY:roadConcrete  13.750      1.724   7.976 1.43e-08 ***
brandX:roadConcrete   6.500      1.724   3.770  0.00081 ***
brandY:roadAsphalt    9.000      1.724   5.220 1.69e-05 ***
brandX:roadAsphalt    4.750      1.724   2.755  0.01037 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.724 on 27 degrees of freedom
Multiple R-squared:  0.8808,  Adjusted R-squared:  0.8454
F-statistic: 24.93 on 8 and 27 DF,  p-value: 1.479e-10

> anova.tire2 <- aov(fit.tire2)
> summary(anova.tire2)
            Df Sum Sq Mean Sq F value   Pr(>F)
brand        2 155.39   77.69   26.14 4.84e-07 ***
road         2 241.72  120.86   40.66 7.15e-09 ***
brand:road   4 195.61   48.90   16.45 6.09e-07 ***
Residuals   27  80.25    2.97
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

library(sjPlot)
plot_model(fit.tire)
```



##Centralization##

model.matrix(fit.tire) #X and Asphalt as reference level

	(Intercept)	brandY	brandZ	roadConcrete	roadGravel	brandY:roadConcrete	brandZ:roadConcrete
1	1	0	0	0	0	0	0
2	1	0	0	0	0	0	0
3	1	0	0	0	0	0	0
4	1	0	0	0	0	0	0
5	1	1	0	0	0	0	0
6	1	1	0	0	0	0	0
7	1	1	0	0	0	0	0
8	1	1	0	0	0	0	0
9	1	0	1	0	0	0	0
10	1	0	1	0	0	0	0
11	1	0	1	0	0	0	0
12	1	0	1	0	0	0	0
13	1	0	0	1	0	0	0
14	1	0	0	1	0	0	0
15	1	0	0	1	0	0	0
16	1	0	0	1	0	0	0
17	1	1	0	1	0	1	0
18	1	1	0	1	0	1	0
19	1	1	0	1	0	1	0

20	1	1	0	1	0	1	0
21	1	0	1	1	0	0	1
22	1	0	1	1	0	0	1
23	1	0	1	1	0	0	1
24	1	0	1	1	0	0	1
25	1	0	0	0	1	0	0
26	1	0	0	0	1	0	0
27	1	0	0	0	1	0	0
28	1	0	0	0	1	0	0
29	1	1	0	0	1	0	0
30	1	1	0	0	1	0	0
31	1	1	0	0	1	0	0
32	1	1	0	0	1	0	0
33	1	0	1	0	1	0	0
34	1	0	1	0	1	0	0
35	1	0	1	0	1	0	0
36	1	0	1	0	1	0	0

	brandY:roadGravel	brandZ:roadGravel
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0

```
19              0              0
20              0              0
21              0              0
22              0              0
23              0              0
24              0              0
25              0              0
26              0              0
27              0              0
28              0              0
29              1              0
30              1              0
31              1              0
32              1              0
33              0              1
34              0              1
35              0              1
36              0              1
attr(,"assign")
[1] 0 1 1 2 2 3 3 3 3
attr(,"contrasts")
attr(,"contrasts")$brand
[1] "contr.treatment"

attr(,"contrasts")$road
[1] "contr.treatment"

## Brand Y and Concrete as reference level
> model.matrix(fit.tire1)
   (Intercept) brandX brandZ roadAsphalt roadGravel brandX:roadAsphalt brandZ:roadAsphalt
1            1      1      0           1          0                  1                  0
2            1      1      0           1          0                  1                  0
3            1      1      0           1          0                  1                  0
4            1      1      0           1          0                  1                  0
5            1      0      0           1          0                  0                  0
6            1      0      0           1          0                  0                  0
```

7	1	0	0	1	0	0	0
8	1	0	0	1	0	0	0
9	1	0	1	1	0	0	1
10	1	0	1	1	0	0	1
11	1	0	1	1	0	0	1
12	1	0	1	1	0	0	1
13	1	1	0	0	0	0	0
14	1	1	0	0	0	0	0
15	1	1	0	0	0	0	0
16	1	1	0	0	0	0	0
17	1	0	0	0	0	0	0
18	1	0	0	0	0	0	0
19	1	0	0	0	0	0	0
20	1	0	0	0	0	0	0
21	1	0	1	0	0	0	0
22	1	0	1	0	0	0	0
23	1	0	1	0	0	0	0
24	1	0	1	0	0	0	0
25	1	1	0	0	1	0	0
26	1	1	0	0	1	0	0
27	1	1	0	0	1	0	0
28	1	1	0	0	1	0	0
29	1	0	0	0	1	0	0
30	1	0	0	0	1	0	0
31	1	0	0	0	1	0	0
32	1	0	0	0	1	0	0
33	1	0	1	0	1	0	0
34	1	0	1	0	1	0	0
35	1	0	1	0	1	0	0
36	1	0	1	0	1	0	0

	brandX:roadGravel	brandZ:roadGravel
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0

```
6    0    0
7    0    0
8    0    0
9    0    0
10   0    0
11   0    0
12   0    0
13   0    0
14   0    0
15   0    0
16   0    0
17   0    0
18   0    0
19   0    0
20   0    0
21   0    0
22   0    0
23   0    0
24   0    0
25   1    0
26   1    0
27   1    0
28   1    0
29   0    0
30   0    0
31   0    0
32   0    0
33   0    1
34   0    1
35   0    1
36   0    1
attr(,"assign")
[1] 0 1 1 2 2 3 3 3 3
attr(,"contrasts")
attr(,"contrasts")$brand
[1] "contr.treatment"
```

```
attr(,"contrasts")$road
[1] "contr.treatment"
attr(,"contrasts")$road
[1] “contr.treatment"

## Brand Z and Gravel as reference level

> model.matrix(fit.tire2)
 (Intercept) brandY brandX roadConcrete roadAsphalt brandY:roadConcrete
brandX:roadConcrete
1    1  0  1   0   1    0    0
2    1  0  1   0   1    0    0
3    1  0  1   0   1    0    0
4    1  0  1   0   1    0    0
5    1  1  0   0   1    0    0
6    1  1  0   0   1    0    0
7    1  1  0   0   1    0    0
8    1  1  0   0   1    0    0
9    1  0  0   0   1    0    0
10   1  0  0   0   1    0    0
11   1  0  0   0   1    0    0
12   1  0  0   0   1    0    0
13   1  0  1   1   0    0    1
14   1  0  1   1   0    0    1
15   1  0  1   1   0    0    1
16   1  0  1   1   0    0    1
17   1  1  0   1   0    1    0
18   1  1  0   1   0    1    0
19   1  1  0   1   0    1    0
20   1  1  0   1   0    1    0
21   1  0  0   1   0    0    0
22   1  0  0   1   0    0    0
23   1  0  0   1   0    0    0
24   1  0  0   1   0    0    0
25   1  0  1   0   0    0    0
```

26	1	0	1	0	0	0	0
27	1	0	1	0	0	0	0
28	1	0	1	0	0	0	0
29	1	1	0	0	0	0	0
30	1	1	0	0	0	0	0
31	1	1	0	0	0	0	0
32	1	1	0	0	0	0	0
33	1	0	0	0	0	0	0
34	1	0	0	0	0	0	0
35	1	0	0	0	0	0	0
36	1	0	0	0	0	0	0

	brandY:roadAsphalt	brandX:roadAsphalt
1	0	1
2	0	1
3	0	1
4	0	1
5	1	0
6	1	0
7	1	0
8	1	0
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	0	0
20	0	0
21	0	0
22	0	0
23	0	0
24	0	0

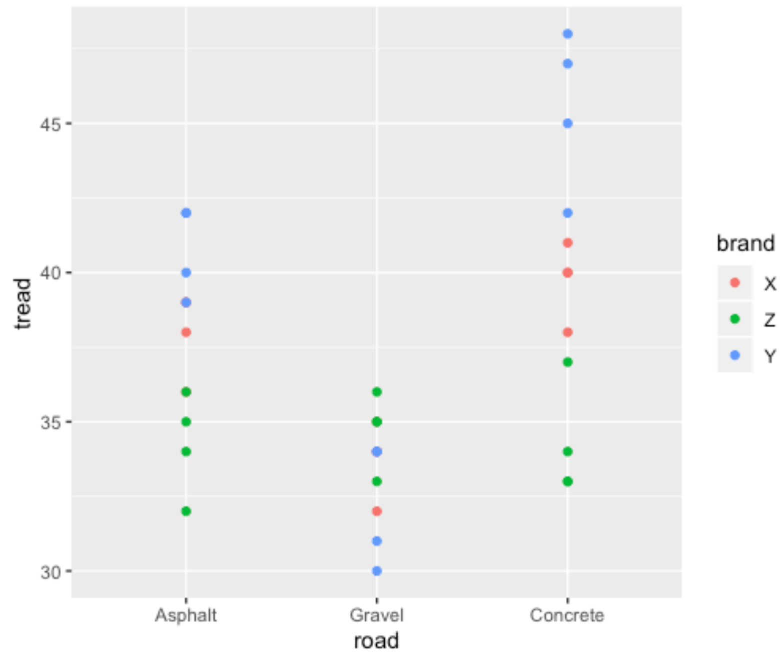
25	0	0
26	0	0
27	0	0
28	0	0
29	0	0
30	0	0
31	0	0
32	0	0
33	0	0
34	0	0
35	0	0
36	0	0

attr(,"assign")
[1] 0 1 1 2 2 3 3 3 3
attr(,"contrasts")
attr(,"contrasts")$brand
[1] "contr.treatment"

attr(,"contrasts")$road
[1] “contr.treatment"

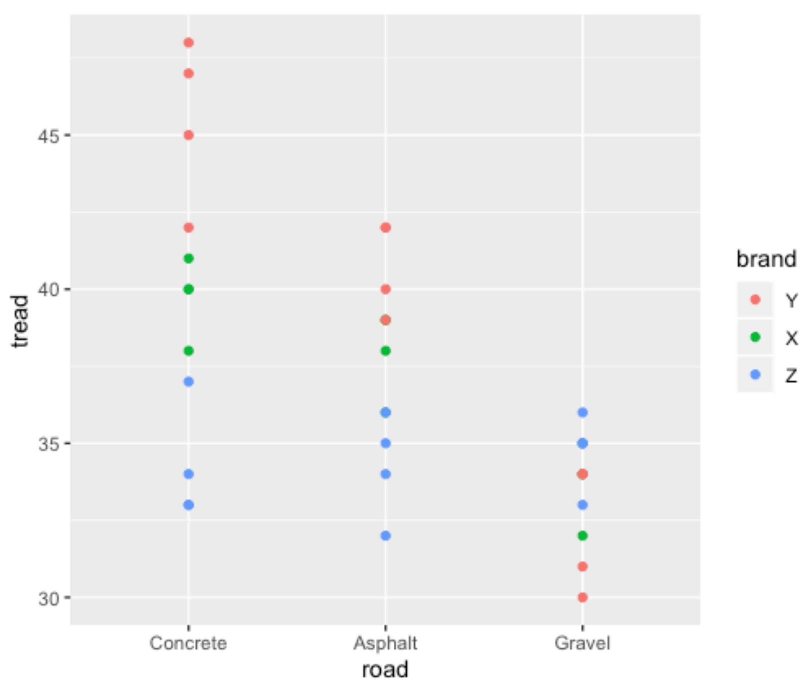
X and Asphalt as reference level:

```
library(ggplot2)
#Scatterplot of all factors X, Y, and Z, and Asphalt, Concrete, and Gravel against tread
tire$brand <- relevel(tire$brand, ref = "X")
tire$road <- relevel(tire$road, ref = "Asphalt")
ggplot(tire, aes(x = road, y = tread)) +
  geom_point(aes(color = brand))
```



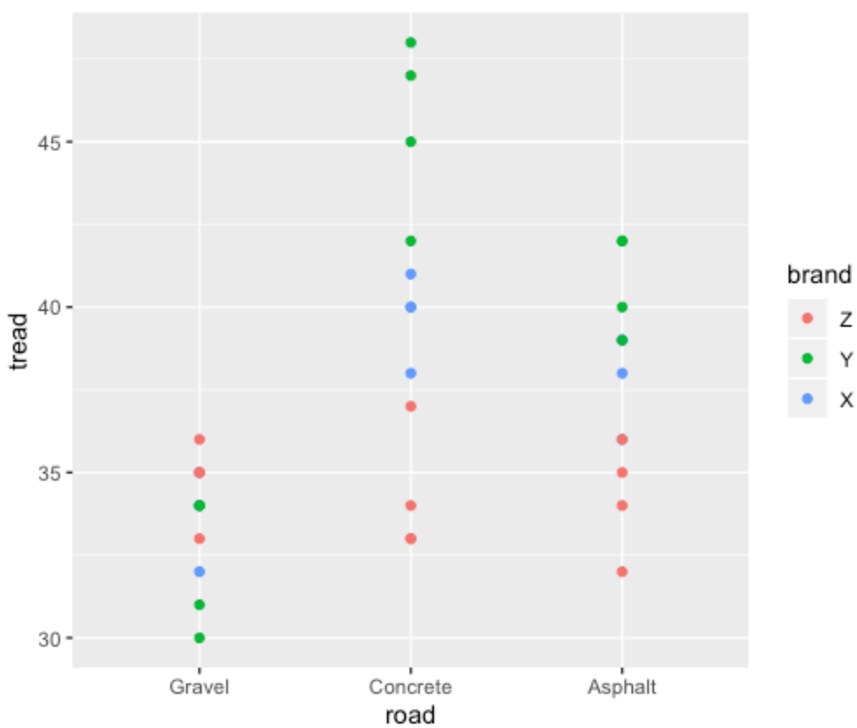
Y and Concrete as reference level:

```
## Brand Y and Concrete as reference level
tire$brand <- relevel(tire$brand, ref = "Y")
tire$road <- relevel(tire$road, ref = "Concrete")
ggplot(tire, aes(x = road, y = tread)) +
  geom_point(aes(color = brand))
```

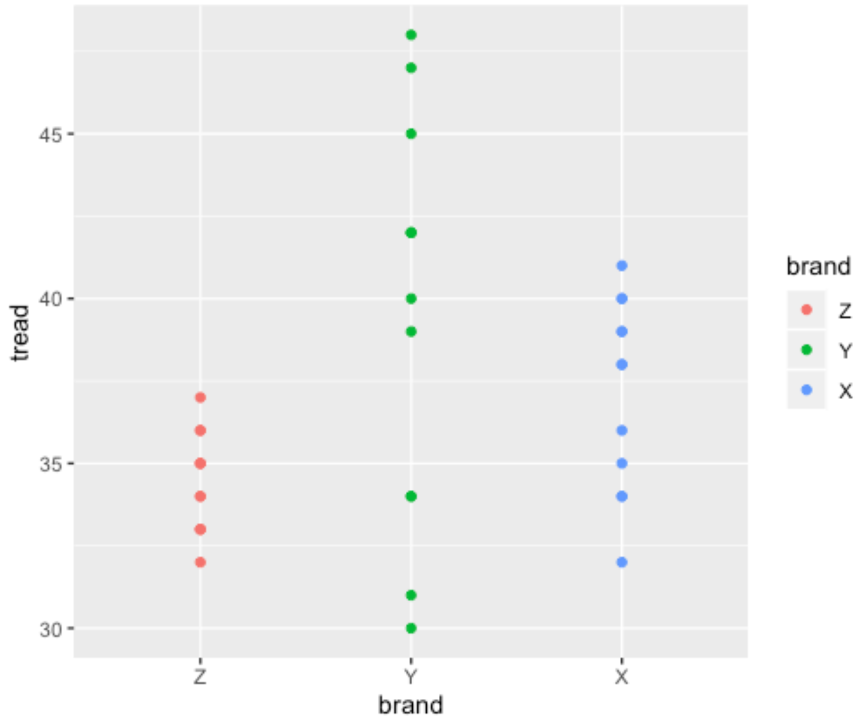


Z and Gravel as reference level:

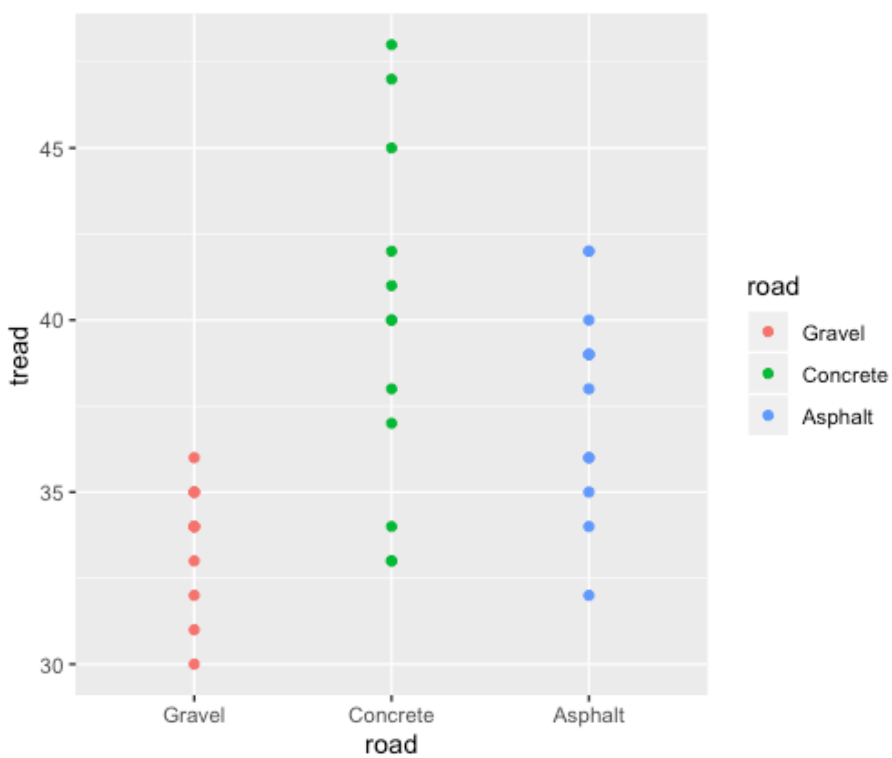
```
## Brand Z and Gravel as reference level
tire$brand <- relevel(tire$brand, ref = "Z")
tire$road <- relevel(tire$road, ref = "Gravel")
ggplot(tire, aes(x = road, y = tread)) +
  geom_point(aes(color = brand))
```




```
#Scatterplot of factors X, Y, and Z, and tread
ggplot(tire, aes(x = brand, y = tread)) +
  geom_point(aes(color=brand))
```




```
#Scatterplot of road factor
ggplot(tire, aes(x = road, y = tread)) +
  geom_point(aes(color=road))
```



There is an interaction effect among the road type and tire brand.

```
install.packages(caret)
library(caret)
dmy <- dummyVars(~ brand + road, data=tire, fullRank=T)
View(dmy)
dummy <- data.frame(predict(dmy, tire), tread)
View(dummy)
View(when)
dummy.lm <- lm(tread ~ brand + road, data = dummy)
summary(dummy.lm)
Call:
lm(formula = tread ~ brand + road, data = dummy)

Residuals:
    Min      1Q  Median      3Q     Max
-6.0556 -1.8472  0.0278  1.4236  5.6944

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)    37.806      1.112  34.006  < 2e-16 ***
brandY          2.333      1.218   1.916  0.06463 .
brandZ         -2.750      1.218  -2.258  0.03112 *
roadConcrete    2.167      1.218   1.779  0.08503 .
roadGravel     -4.083      1.218  -3.353  0.00212 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.983 on 31 degrees of freedom
Multiple R-squared:  0.5901,  Adjusted R-squared:  0.5372
F-statistic: 11.16 on 4 and 31 DF,  p-value: 1.007e-05

dummy.aov <- aov(dummy.lm)
summary(dummy.aov)
> summary(dummy.aov)
            Df Sum Sq Mean Sq F value   Pr(>F)
```

```
brand        2  155.4   77.69   8.731 0.000983 ***
road         2  241.7  120.86  13.582 5.81e-05 ***
Residuals   31  275.9    8.90
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> plot_model(dummy.lm)
```