HW4

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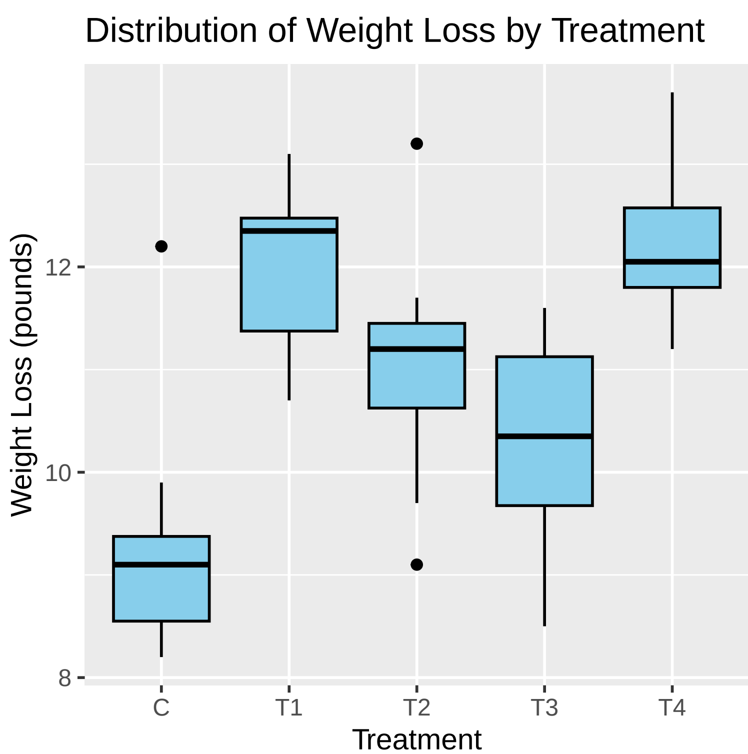
Problem 1

Problem 1(a)

```
## # A tibble: 5 x 4
##   Trt   sample_size mean_weight_loss sd_weight_loss
##   <chr>       <int>            <dbl>          <dbl>
## 1 C              10             9.27          1.16
## 2 T1             10            12.0           0.829
## 3 T2             10            11.0           1.12
## 4 T3             10            10.3           1.03
## 5 T4             10            12.2           0.756
```

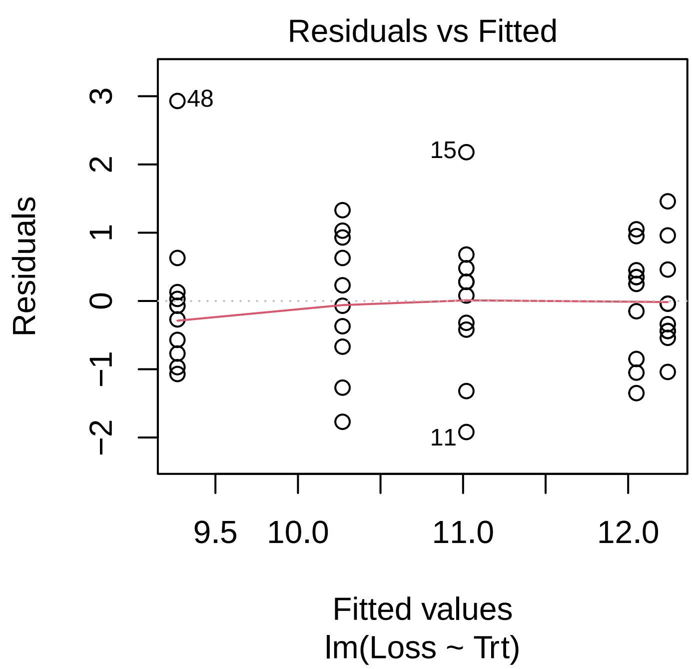
Problem 1(b)

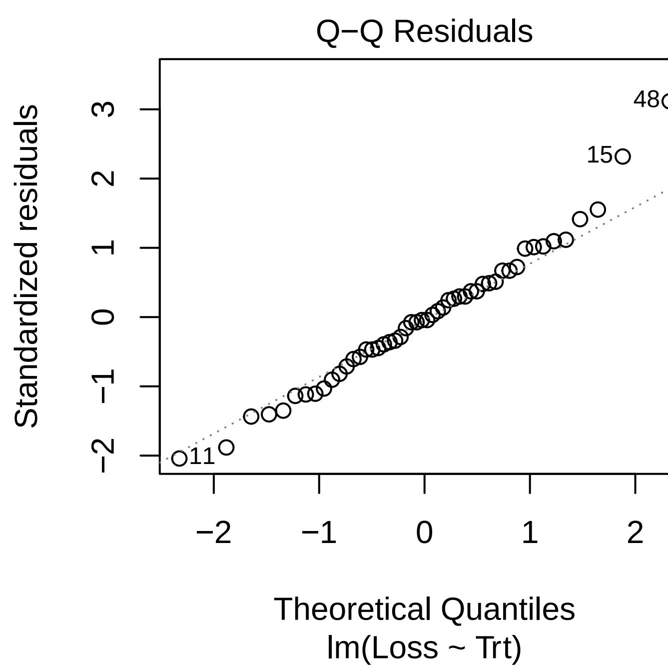


Problem 1(c)

```
## Analysis of Variance Table
##
## Response: Loss
##           Df Sum Sq Mean Sq F value    Pr(>F)
## Trt        4 61.618 15.4045  15.681 4.164e-08 ***
## Residuals 45 44.207  0.9824
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Problem 1(d)





I have concerns with the residuals v.s. fitted values plot due to the fact that the points are not randomly scattered around the horizontal line at 0 and that it dips down at the beginning of the plot. Therefore I would question the constant variance of the data.

Problem 1(e)

```
##  Trt emmean    SE df lower.CL upper.CL
```

```
##  C      9.27 0.313 45     8.64      9.9
##  T1    12.05 0.313 45    11.42     12.7
##  T2    11.02 0.313 45    10.39     11.7
##  T3    10.27 0.313 45     9.64     10.9
##  T4    12.24 0.313 45    11.61     12.9
##
## Confidence level used: 0.95
```

Problem 1(f)

```
##  contrast estimate    SE df t.ratio p.value
##  C - T1      -2.78 0.443 45  -6.272  <.0001
##  C - T2      -1.75 0.443 45  -3.948  0.0003
##  C - T3      -1.00 0.443 45  -2.256  0.0290
##  C - T4      -2.97 0.443 45  -6.700  <.0001
##  T1 - T2      1.03 0.443 45   2.324  0.0247
##  T1 - T3      1.78 0.443 45   4.016  0.0002
##  T1 - T4     -0.19 0.443 45  -0.429  0.6702
##  T2 - T3      0.75 0.443 45   1.692  0.0976
##  T2 - T4     -1.22 0.443 45  -2.752  0.0085
##  T3 - T4     -1.97 0.443 45  -4.444  0.0001
```

Problem 1(g)

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = Loss ~ Trt, data = df)
##
## $Trt
##        diff        lwr        upr     p adj
## T1-C   2.78  1.5205113  4.0394887 0.0000012
## T2-C   1.75  0.4905113  3.0094887 0.0024286
## T3-C   1.00 -0.2594887  2.2594887 0.1784060
## T4-C   2.97  1.7105113  4.2294887 0.0000003
## T2-T1 -1.03 -2.2894887  0.2294887 0.1563263
## T3-T1 -1.78 -3.0394887 -0.5205113 0.0019803
## T4-T1  0.19 -1.0694887  1.4494887 0.9927171
## T3-T2 -0.75 -2.0094887  0.5094887 0.4490082
## T4-T2  1.22 -0.0394887  2.4794887 0.0617607
## T4-T3  1.97  0.7105113  3.2294887 0.0005243
```

Problem 1(h)

```
##
```

```
##  Pairwise comparisons using t tests with pooled SD
##
## data:  df$Loss and df$Trt
##
##    C       T1      T2      T3
## T1 1.2e-06 -       -       -
## T2 0.00274 0.24716 -       -
## T3 0.28975 0.00222 0.97555 -
## T4 2.8e-07 1.00000 0.08499 0.00057
##
## P value adjustment method: bonferroni
```

Problem 1(i)

Tukey and Bonferri control the family wise error rate. Unadjusted p-values do not control the family wise error rate.

Problem 1(j)

Tukey's adjusted pairwise comparison has the higher power compared to Bonferroni, this is because Tukey's is less conservative allowing for more comparisons to be detected.

Problem 1(k)

```
##
##   Simultaneous Tests for General Linear Hypotheses
##
## Multiple Comparisons of Means: Dunnett Contrasts
##
##
## Fit: aov(formula = Loss ~ Trt, data = df)
##
## Linear Hypotheses:
##             Estimate Std. Error t value Pr(>|t|)
## T1 - C == 0   2.7800     0.4433   6.272   <0.001 ***
## T2 - C == 0   1.7500     0.4433   3.948   <0.001 ***
## T3 - C == 0   1.0000     0.4433   2.256    0.093 .
## T4 - C == 0   2.9700     0.4433   6.700   <0.001 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
```

```
## [1] 3.608014e-07 9.501467e-04 9.313235e-02 5.283771e-08
## attr(,"error")
## [1] 0.0002286555
```

Problem 2(a)

The main benefit for using a multiple testing adjustment is to control the Family Wise Error Rate. The FWER is the probability of making atleast one Type 1 Error. When we adjust we can maintain the error rate across comparisons.

Problem 2(b)

The main limitation of using a multiple testing adjustment is that it increases the odds of getting a Type 2 Error.

Problem 3(a)

Using no adjustment tests A,C,D,E,F,H, and I reject the null hypothesis at alpha = 0.05.

Problem 3(b)

For Bonferroni I divided 0.05 /10 so tests A,H, and C have p-values less than adjusted p-value 0.005

Problem 3(c)

For Holm-Bonferroni assort in ascending order and go down the list and determine what value is less than 0.005/ k - i. We determine A is less than 0.005 but B is not so we stop.

Problem 3(d)

Tests A,C,H,D, and I reject the null hypothesis. I ordered p-values in ascending order and then I divided alpha by its position with top starting at 1. (i.e. critical value for A is (1/10) * 0.05 and critical value for G is (10/10) * 0.05)

Problem 3(e)

Benjamini-Hochberg has the highest power because it has the most rejected null hypotheses.

Problem 3(f)

Tukey adjustment is approporiate when there are 3 or more groups being analyzed, and the groups have equal sample sizes. Tukey does well in maintaining balance between Type 1 Error rate and increasing power.

Problem 3(g)

```
##    Unadjusted Bonferroni   Holm     BH_FDR
## 1     0.00003     0.0003 0.0003 0.00030000
## 2     0.04800     0.4800 0.0960 0.05333333
## 3     0.00170     0.0170 0.0153 0.00850000
## 4     0.00720     0.0720 0.0504 0.01560000
```

```
## 5     0.01610     0.1610 0.0650 0.02012500
## 6     0.01300     0.1300 0.0650 0.02012500
## 7     0.12900     1.0000 0.1290 0.12900000
## 8     0.00440     0.0440 0.0352 0.01466667
## 9     0.00780     0.0780 0.0504 0.01560000
## 10    0.01550     0.1550 0.0650 0.02012500
```

Appendix

```r
library(knitr)
# install the tidyverse library (do this once) install.packages('tidyverse')
library(tidyverse)
knitr::opts_chunk$set(echo = FALSE, message = FALSE, warning = FALSE, fig.width = 4,
    fig.height = 4, tidy = TRUE)
df <- read_csv("WtLoss.csv")

summary_stats <- df %>%
    group_by(Trt) %>%
    summarise(sample_size = n(), mean_weight_loss = mean(Loss), sd_weight_loss = sd(Loss))

summary_stats
ggplot(df, aes(x = Trt, y = Loss)) + geom_boxplot(fill = "skyblue", color = "black") +
    labs(x = "Treatment", y = "Weight Loss (pounds)", title = "Distribution of Weight Loss by Treatment
lmr <- lm(Loss ~ Trt, data = df)
model <- anova(lmr)
model
plot(lmr, which = 1)

plot(lmr, which = 2)
library(emmeans)
emmeans(lmr, "Trt")
df$Trt <- as.factor(df$Trt)
lmOut <- lm(Loss ~ Trt, data = df)
mse <- anova(lmOut)[2, 3]
y1bar <- lmOut$fitted.values[1]
y2bar <- lmOut$fitted.values[6]
emmeansOut <- emmeans(lmOut, specs = "Trt")
pairs(emmeansOut, adjust = "none")
model <- aov(Loss ~ Trt, data = df)

tukey_result <- TukeyHSD(model)

tukey_result

bonferroni_results <- pairwise.t.test(df$Loss, df$Trt, p.adjust.method = "bonferroni")

bonferroni_results
```

```r
library(multcomp)

dunnett_result <- glht(model, linfct = mcp(Trt = "Dunnett"))

summary(dunnett_result)

adjusted_p_values <- summary(dunnett_result)$test$pvalues

adjusted_p_values








p_unadjusted <- c(3e-05, 0.048, 0.0017, 0.0072, 0.0161, 0.013, 0.129, 0.0044, 0.0078,
    0.0155)

p_bonferroni <- p.adjust(p_unadjusted, method = "bonferroni")

p_holm <- p.adjust(p_unadjusted, method = "holm")

p_bh <- p.adjust(p_unadjusted, method = "fdr")

adjustments <- data.frame(Unadjusted = p_unadjusted, Bonferroni = p_bonferroni, Holm = p_holm,
    BH_FDR = p_bh)

adjustments
```