6: Lab - Generalized Linear Models

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Objectives

1. Answer questions on M5/A5
2. Answer questions on M6 - GLMs
3. Practice more application GLM to real datasets

Set up

```
library(tidyverse)
library(agricolae)
library(here)
here()
```

```
## [1] "/home/guest/EDA/EDA-Spring2023"
```

```
EPAair <- read.csv(here("Data/Processed_KEY/EPAair_O3_PM25_NC1819_Processed.csv"), stringsAsFactors = TR
# Set date to date format
EPAair$Date <- as.Date(EPAair$Date, format = "%Y-%m-%d")

Litter <- read.csv(here("Data/Processed_KEY/NEON_NIWO_Litter_mass_trap_Processed.csv"), stringsAsFactors
# Set date to date format
Litter$collectDate <- as.Date(Litter$collectDate , format = "%Y-%m-%d")

# Set theme
mytheme <- theme_classic(base_size = 14) +
  theme(axis.text = element_text(color = "black"),
        legend.position = "top")
theme_set(mytheme)
```

Visualization and interpretation challenge

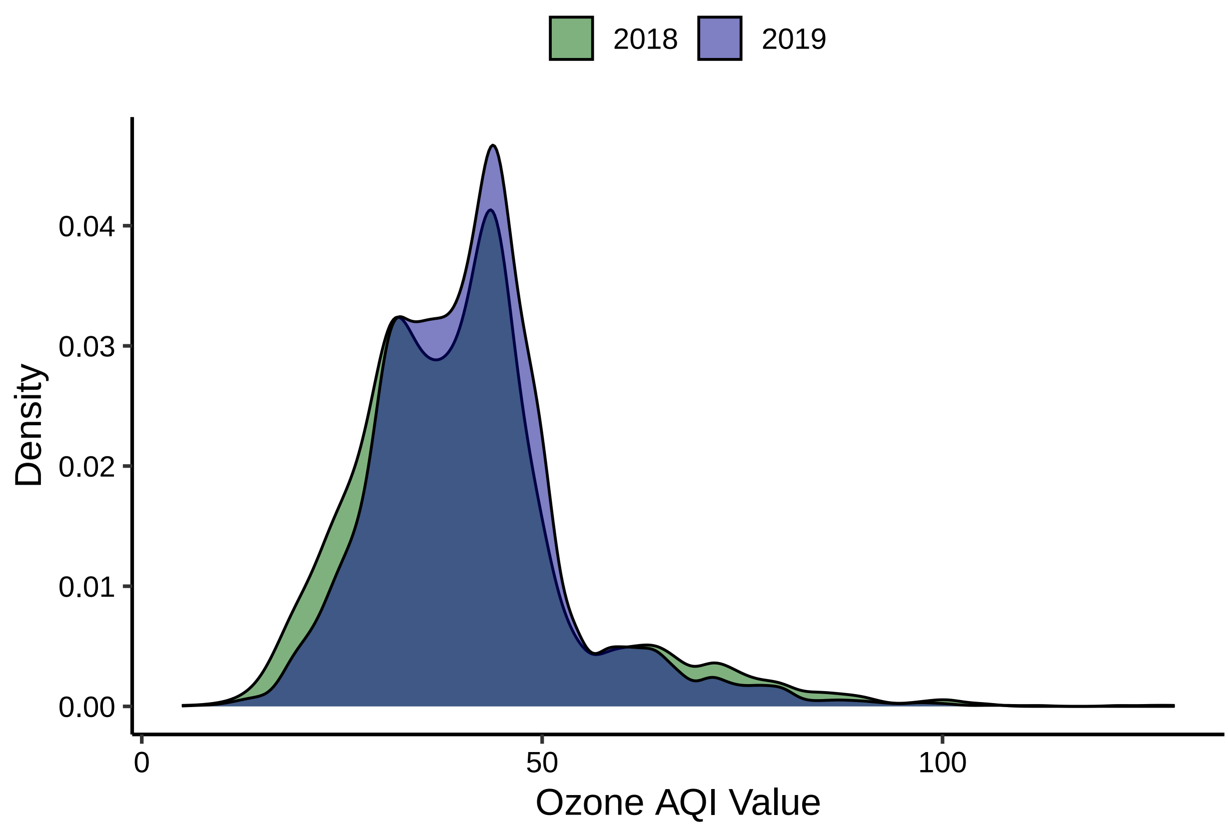
Create three plots, each with appropriately formatted axes and legends. Choose a non-default color palette.

1. geom_density of ozone divided by year (distinguish between years by adding transparency to the geom_density layer).
2. geom_boxplot of ozone divided by year. Add letters representing a significant difference between 2018 and 2019 (hint: stat_summary).

3. geom_violin of ozone divided by year, with the 0.5 quantile marked as a horizontal line. Add letters representing a significant difference between 2018 and 2019.

```
#Exercise 1:
O3.density <- ggplot(EPAair,aes(x=Ozone, fill = as.factor(Year))) +
  geom_density(alpha=.5) +
  scale_fill_manual(values=c("darkgreen", "darkblue"))+
  labs(x="Ozone AQI Value", y="Density", fill="")
print(O3.density)
```

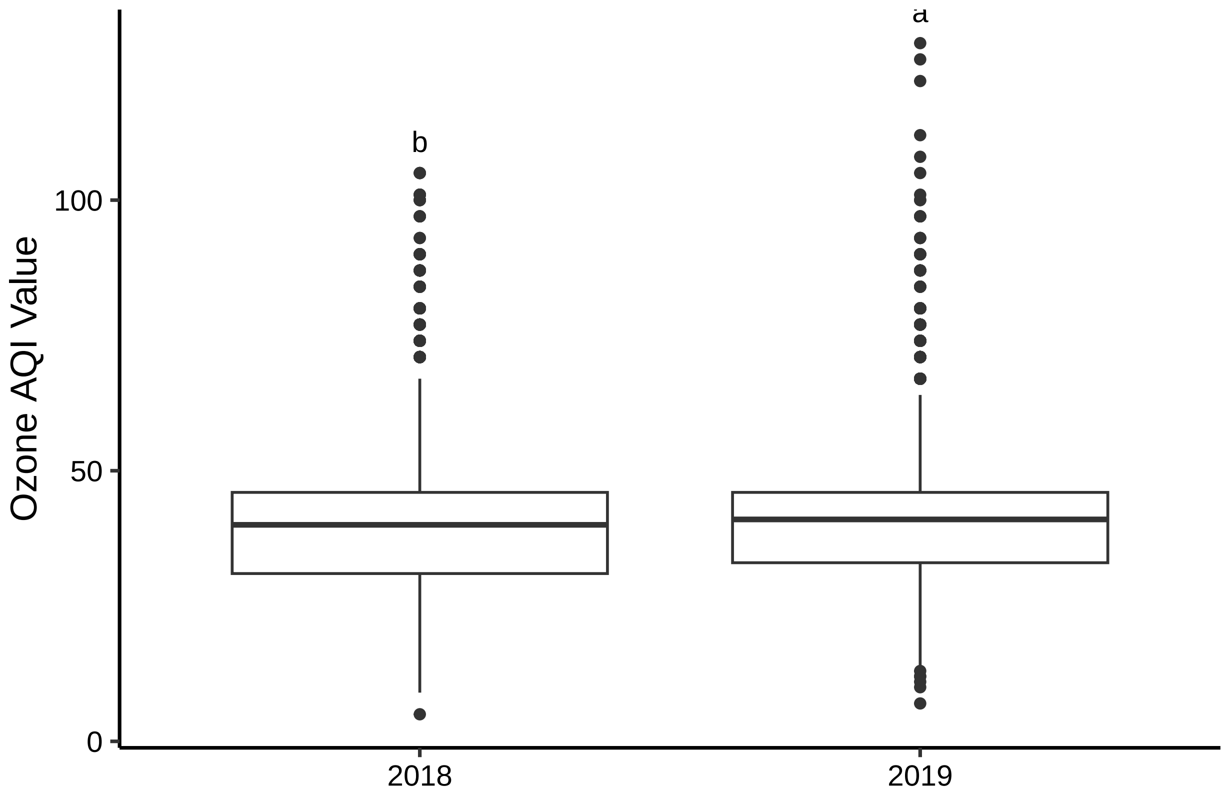
```
## Warning: Removed 2146 rows containing non-finite values (`stat_density()`).
```




```
O3.boxplot <- ggplot(EPAair,aes(x=as.factor(Year),y=Ozone)) +
  geom_boxplot() +
  stat_summary(geom="text",fun=max,vjust=-1,size=4,label=c("b","a")) +
  labs(x="", y="Ozone AQI Value")
print(O3.boxplot)
```

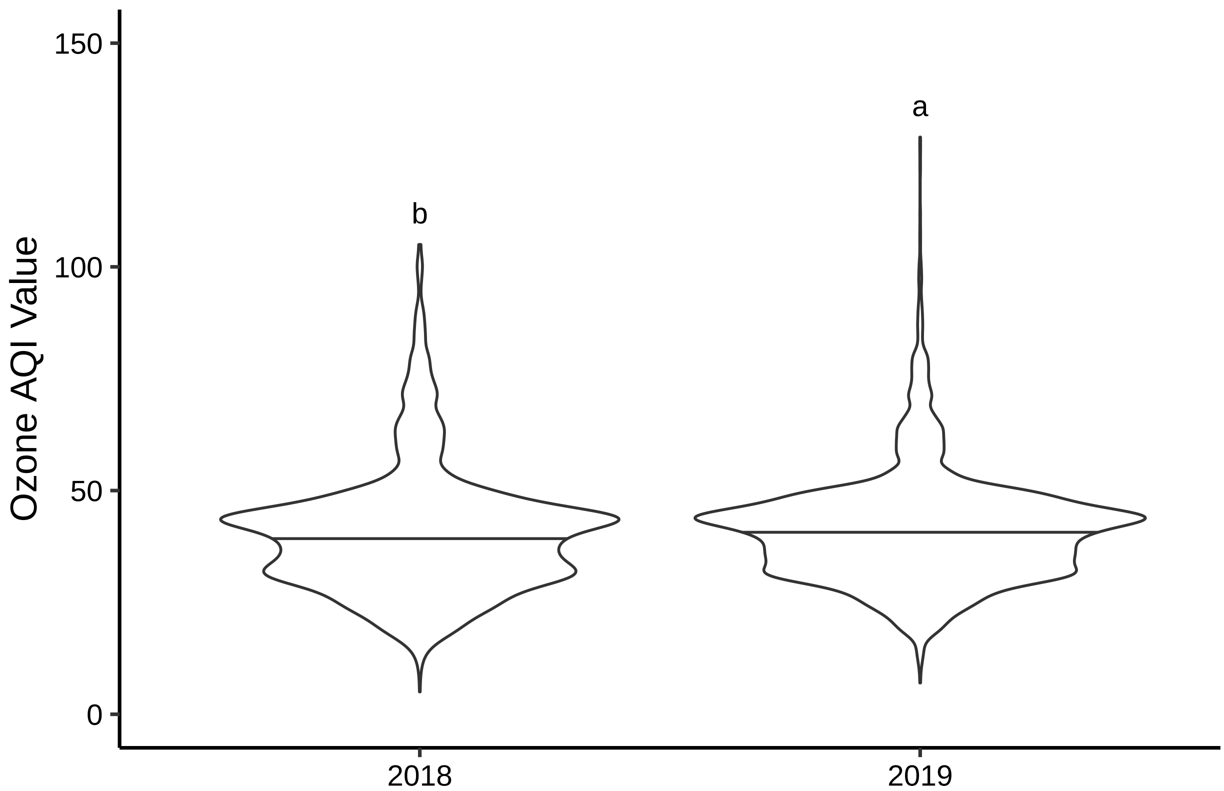
```
## Warning: Removed 2146 rows containing non-finite values (`stat_boxplot()`).
```

```
## Warning: Removed 2146 rows containing non-finite values (`stat_summary()`).
```




```
O3.violin <- ggplot(EPAair,aes(x=as.factor(Year),y=Ozone)) +
  geom_violin(draw_quantiles = 0.5) +
  stat_summary(geom="text",fun=max,vjust=-1,size=4,label=c("b","a")) +
  labs(x="", y="Ozone AQI Value") +
  ylim(0,150)
print(O3.violin)
```

```
## Warning: Removed 2146 rows containing non-finite values (`stat_ydensity()`).
## Removed 2146 rows containing non-finite values (`stat_summary()`).
```



Linear Regression

Important components of the linear regression are the correlation and the R-squared value. The **correlation** is a number between -1 and 1, describing the relationship between the variables. Correlations close to -1 represent strong negative correlations, correlations close to zero represent weak correlations, and correlations close to 1 represent strong positive correlations. The **R-squared value** is the correlation squared, becoming a number between 0 and 1. The R-squared value describes the percent of variance accounted for by the explanatory variables.

For the NTL-LTER dataset, can we predict PM2.5 from Ozone?

```
#Exercise 2: Run a linear regression PM2.5 by Ozone. Find the p-value and R-squared value.
PMbyOzone <- lm(data=EPAair,PM2.5 ~ Ozone)
summary(PMbyOzone)
```

```
##
## Call:
## lm(formula = PM2.5 ~ Ozone, data = EPAair)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -37.204  -8.931  -0.613   8.463  48.473
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) 15.63824    0.55556   28.15   <2e-16 ***
## Ozone        0.38384    0.01298   29.58   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.06 on 5774 degrees of freedom
##   (3200 observations deleted due to missingness)
## Multiple R-squared:  0.1316, Adjusted R-squared:  0.1314
## F-statistic: 874.9 on 1 and 5774 DF,  p-value: < 2.2e-16
```

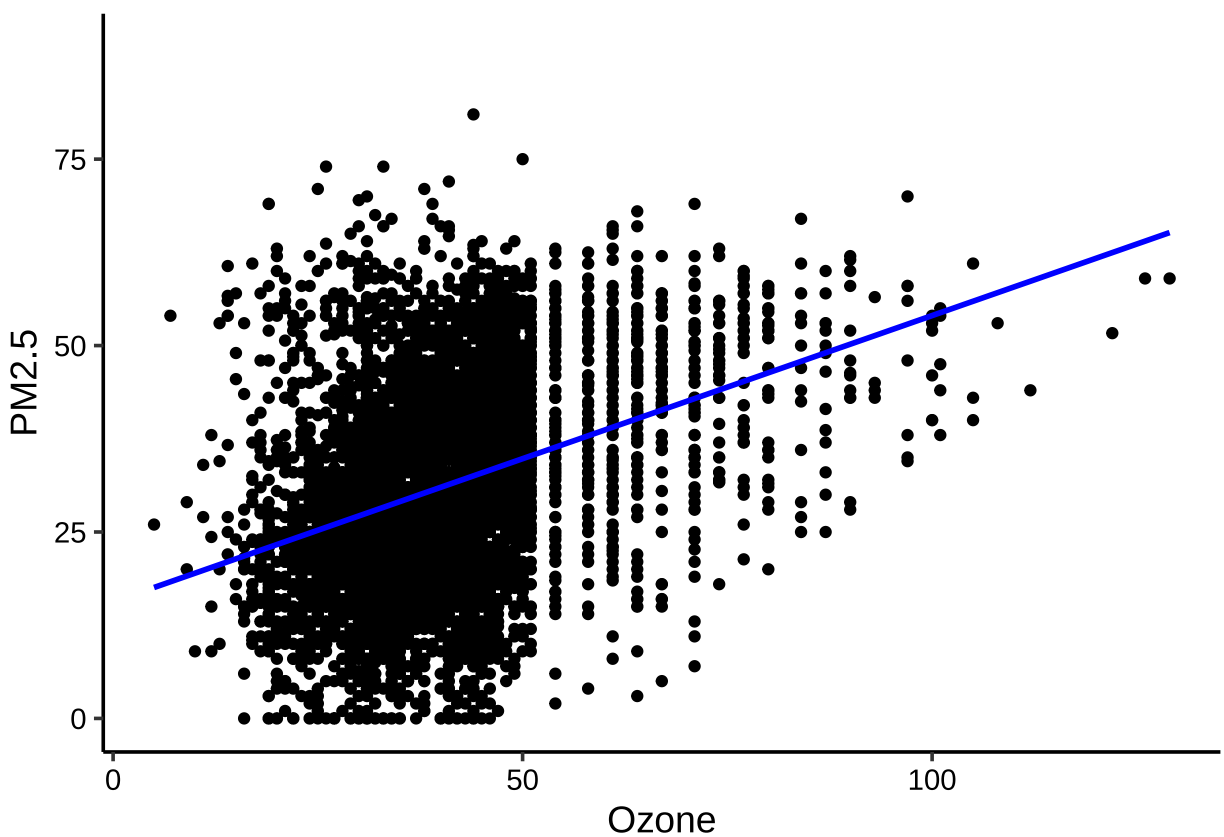
```
#Exercise 3: Build a scatterplot. Add a line and standard error for the linear regression. Add the regr

ggplot(EPAair,aes(x=Ozone, y=PM2.5)) +
  geom_point() +
  geom_smooth(method="lm", col="blue", se=FALSE)
```

```
## `geom_smooth()` using formula = 'y ~ x'

## Warning: Removed 3200 rows containing non-finite values (`stat_smooth()`).

## Warning: Removed 3200 rows containing missing values (`geom_point()`).
```



AIC to select variables

What other variables can we add to improve model?

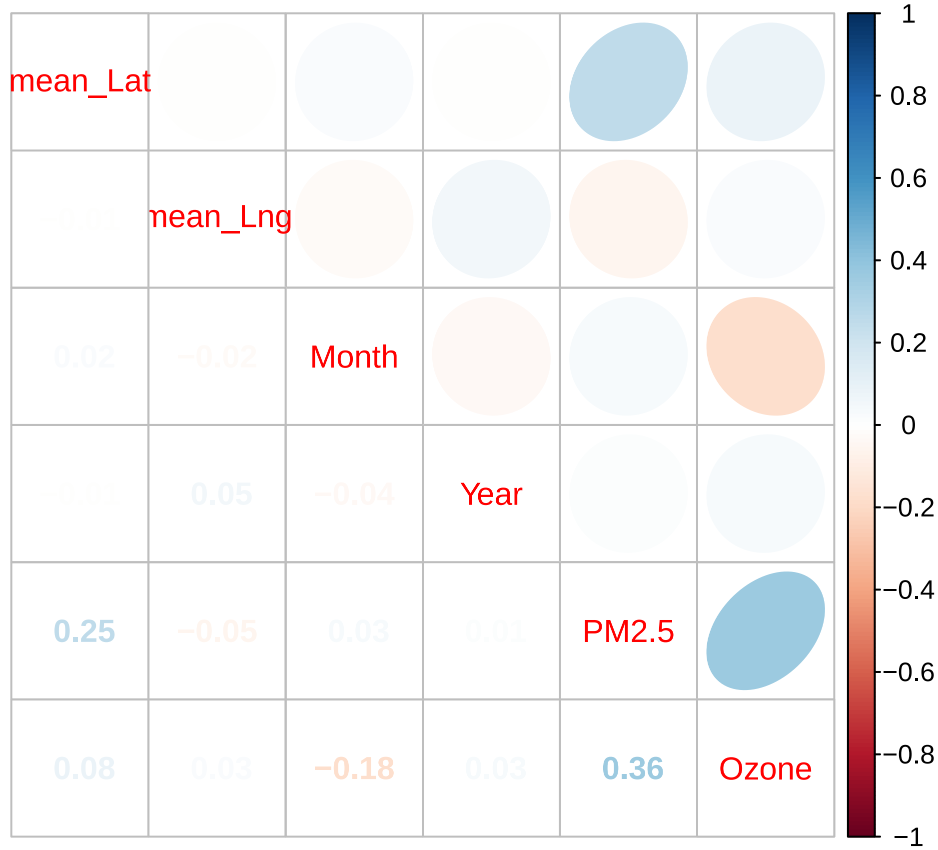
```
#Exercise 4: Build correlation plots and identify more possible explanatory variables to add to the reg

library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
EPAair.subset <-
  EPAair %>%
  select(mean_Lat:Ozone) %>%
  drop_na()

EPAairCorr <- cor(EPAair.subset)
corrplot.mixed(EPAairCorr,upper="ellipse")
```




```
#Exercise 5: Choose a model by AIC in a Stepwise Algorithm. Do the results from AIC match the variables

Ozone.ALL <- lm(data=EPAair.subset, PM2.5 ~ Ozone + Year + Month + mean_Lat + mean_Lng)
summary(Ozone.ALL)
```

```
##
## Call:
## lm(formula = PM2.5 ~ Ozone + Year + Month + mean_Lat + mean_Lng,
##     data = EPAair.subset)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -35.646  -8.837  -0.919   7.798  52.258
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -909.93440  671.49260  -1.355    0.175
## Ozone          0.38226    0.01277  29.930  < 2e-16 ***
## Year           0.32209    0.33233   0.969    0.332
## Month          0.46600    0.06231   7.478 8.64e-14 ***
## mean_Lat       6.52423    0.35277  18.494  < 2e-16 ***
## mean_Lng      -0.50056    0.09863  -5.075 4.00e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.6 on 5770 degrees of freedom
## Multiple R-squared:  0.1927, Adjusted R-squared:  0.192
## F-statistic: 275.5 on 5 and 5770 DF,  p-value: < 2.2e-16
```

```
step(Ozone.ALL)
```

```
## Start:  AIC=29272.11
## PM2.5 ~ Ozone + Year + Month + mean_Lat + mean_Lng
##
##            Df Sum of Sq     RSS   AIC
## - Year      1       149  915695 29271
## <none>                   915545 29272
## - mean_Lng  1      4087  919632 29296
## - Month     1      8874  924420 29326
## - mean_Lat  1     54272  969818 29603
## - Ozone     1    142142 1057688 30104
##
## Step:  AIC=29271.05
## PM2.5 ~ Ozone + Month + mean_Lat + mean_Lng
##
##            Df Sum of Sq     RSS   AIC
## <none>                   915695 29271
## - mean_Lng  1      4017  919712 29294
## - Month     1      8815  924510 29324
## - mean_Lat  1     54223  969918 29601
## - Ozone     1    142470 1058165 30104
```

```
##
## Call:
## lm(formula = PM2.5 ~ Ozone + Month + mean_Lat + mean_Lng, data = EPAair.subset)
##
## Coefficients:
## (Intercept)        Ozone        Month     mean_Lat     mean_Lng
##   -259.2766       0.3826       0.4643       6.5210      -0.4956
```

```
#Exercise 6: Run another regression using the variables selected on Exercise 6. Compare r-squared value

Ozone.best <- lm(data=EPAair, PM2.5 ~ Ozone + Month + mean_Lat + mean_Lng)
summary(Ozone.best) #the more variables you have in your model, the more complex it becomes. so you only
```

```
##
## Call:
## lm(formula = PM2.5 ~ Ozone + Month + mean_Lat + mean_Lng, data = EPAair)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -35.806  -8.846  -0.948   7.777  52.098
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -259.27663   14.74368 -17.586  < 2e-16 ***
## Ozone          0.38257    0.01277  29.965  < 2e-16 ***
## Month          0.46427    0.06229   7.454 1.04e-13 ***
## mean_Lat       6.52098    0.35275  18.486  < 2e-16 ***
## mean_Lng      -0.49563    0.09850  -5.032 5.01e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.6 on 5771 degrees of freedom
##   (3200 observations deleted due to missingness)
## Multiple R-squared:  0.1926, Adjusted R-squared:  0.192
## F-statistic: 344.2 on 4 and 5771 DF,  p-value: < 2.2e-16
```

Litter Exercise

```
# Wrangle the data
Litter.Totals <- Litter %>%
  group_by(plotID, collectDate, nlcdClass) %>%
  summarise(dryMass = sum(dryMass))
```

```
## `summarise()` has grouped output by 'plotID', 'collectDate'. You can override
## using the `.groups` argument.
```

```
# Format ANOVA as aov
Litter.Totals.anova <- aov(data = Litter.Totals, dryMass ~ plotID)
summary(Litter.Totals.anova)
```

```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## plotID       11   7584   689.5   4.813 1.45e-06 ***
## Residuals   198  28363   143.2
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

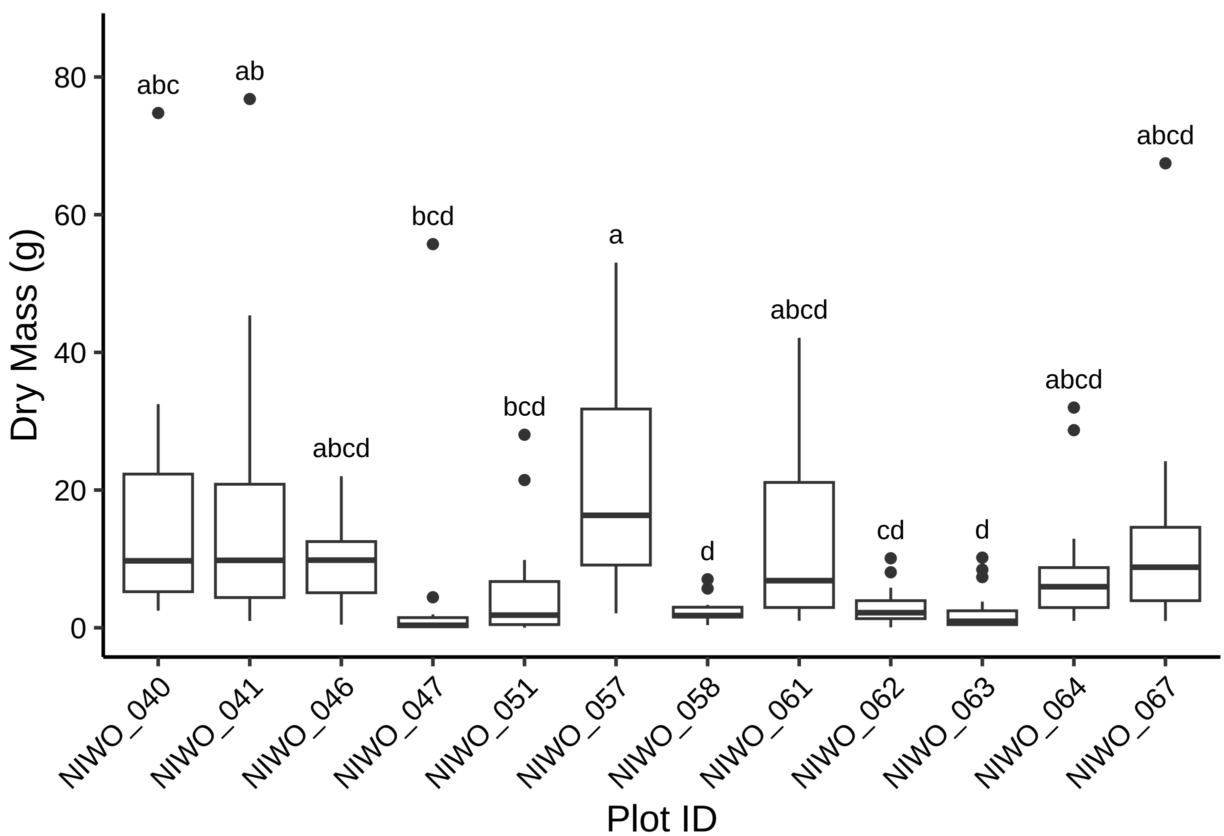
```
# Extract groupings for pairwise relationships
Litter.Totals.groups <- HSD.test(Litter.Totals.anova, "plotID", group = TRUE)
Litter.Totals.groups$groups
```

```
##            dryMass groups
## NIWO_057 20.685833      a
## NIWO_041 16.979063     ab
```

```
## NIWO_040 15.680000    abc
## NIWO_061 13.186111   abcd
## NIWO_067 12.565938   abcd
## NIWO_046  9.956176   abcd
## NIWO_064  8.015789   abcd
## NIWO_051  5.668750    bcd
## NIWO_047  4.476333    bcd
## NIWO_062  3.047632     cd
## NIWO_058  2.398421      d
## NIWO_063  2.393889      d
```

```
Litter.Totals <- Litter.Totals %>%
  mutate( treatgroups = Litter.Totals.groups$groups[plotID,2])

# Graph the results
Litter.Totals.plot <- ggplot(Litter.Totals, aes(x = plotID, y = dryMass)) +
  geom_boxplot() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  stat_summary(geom = "text", fun = max, vjust = -1, size = 3.5,
               label = c("abc", "ab", "abcd", "bcd", "bcd", "a",
                         "d", "abcd", "cd", "d", "abcd", "abcd")) +
  labs(x = "Plot ID", y = "Dry Mass (g)") +
  ylim(0, 85)
print(Litter.Totals.plot)
```



```
#Exercise 7: Improve the plot
```