Assignment 7: GLMs (Linear Regressios, ANOVA, & t-tests)

Student Name

Fall 2023

OVERVIEW

This exercise accompanies the lessons in Environmental Data Analytics on generalized linear models.

Directions

1. Rename this file `<FirstLast>_A07_GLMs.Rmd` (replacing `<FirstLast>` with your first and last name).
2. Change "Student Name" on line 3 (above) with your name.
3. Work through the steps, **creating code and output** that fulfill each instruction.
4. Be sure to **answer the questions** in this assignment document.
5. When you have completed the assignment, **Knit** the text and code into a single PDF file.

Set up your session

1. Set up your session. Check your working directory. Load the tidyverse, agricolae and other needed packages. Import the *raw* NTL-LTER raw data file for chemistry/physics (`NTL-LTER_Lake_ChemistryPhysics_Raw.csv`). Set date columns to date objects.

2. Build a ggplot theme and set it as your default theme.

```
#1
getwd()
```

```
## [1] "Z:/EDE_Fall2023"
```

```
library(tidyverse); library(agricolae); library(lubridate)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.3     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.3     v tibble    3.2.1
## v lubridate 1.9.2     v tidyr     1.3.0
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become error
```

```r
NTL_LTER <- read.csv("./Data/Raw/NTL-LTER_Lake_ChemistryPhysics_Raw.csv")
NTL_LTER$sampledate <- mdy(NTL_LTER$sampledate) #covert to date object
```

```r
#2
my_theme <- theme_classic(base_size = 14) +
  theme(
    line = element_line(linewidth = 2),
    plot.title = element_text(color = "darkgreen"),
    axis.text = element_text(color = "black"),
    axis.ticks = element_line(color = "darkgreen"),
    plot.background = element_rect(color = "black",fill = "gray"),
    legend.position = "top")
theme_set(my_theme)
```

Simple regression

Our first research question is: Does mean lake temperature recorded during July change with depth across all lakes?

3. State the null and alternative hypotheses for this question: > Answer: H0: Lake temperatures recorded during July does not decrease with depth across all lakes. Ha: Lake temperatures recorded during July decrease with depth across all lakes.

4. Wrangle your NTL-LTER dataset with a pipe function so that the records meet the following criteria:

- Only dates in July.
- Only the columns: `lakename`, `year4`, `daynum`, `depth`, `temperature_C`
- Only complete cases (i.e., remove NAs)

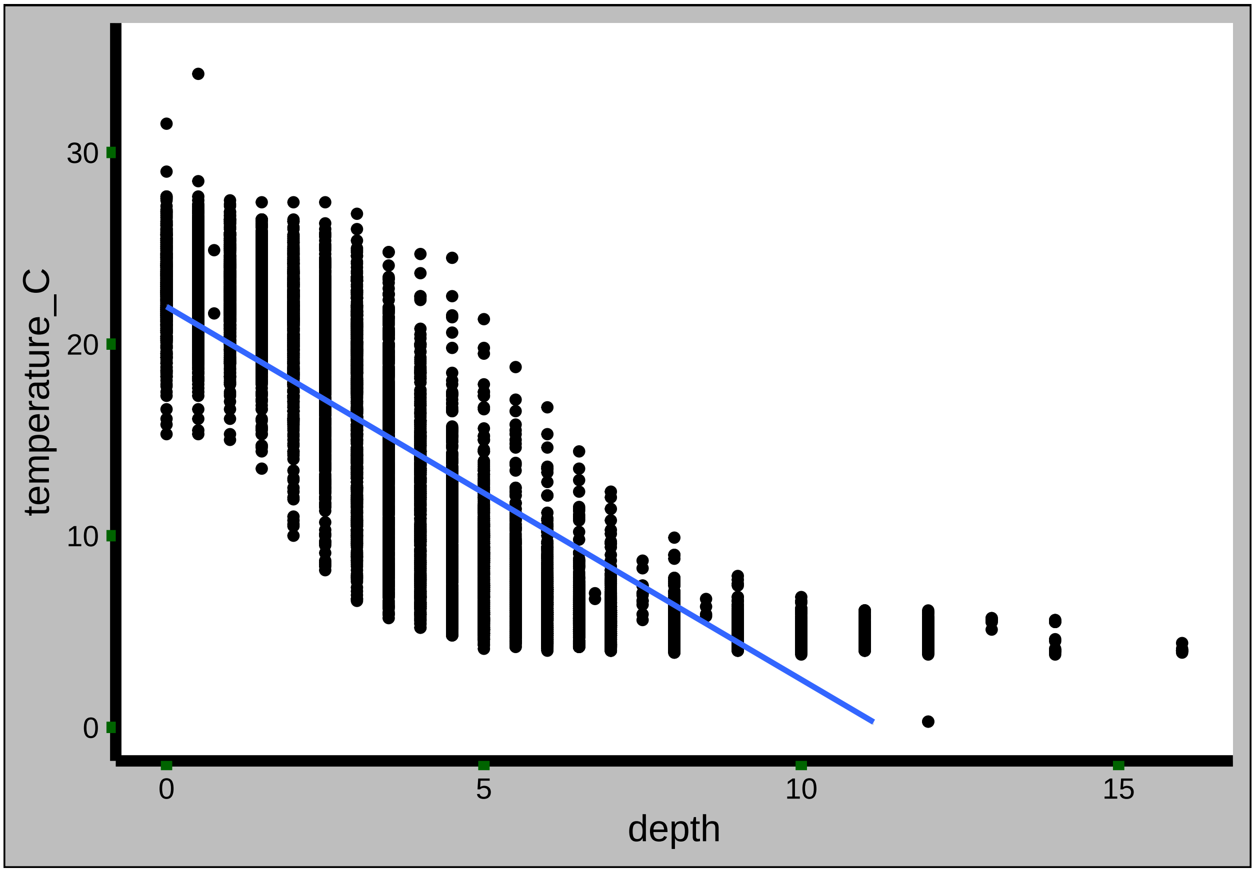
5. Visualize the relationship among the two continuous variables with a scatter plot of temperature by depth. Add a smoothed line showing the linear model, and limit temperature values from 0 to 35 °C. Make this plot look pretty and easy to read.

```r
#4 wrangle NTL-LTER data
NTL_LTER_July <- NTL_LTER %>%
  filter(month(sampledate) %in% 7) %>%
  select(lakename, year4, daynum, depth, temperature_C) %>%
  na.omit()

#5 temp by depth
tempdepth_plot <- ggplot(NTL_LTER_July) +
  geom_point(aes(x = depth, y = temperature_C)) +
  geom_smooth(method = "lm", aes(x = depth, y = temperature_C)) +
  ylim(0, 35)
print(tempdepth_plot)
```

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

```
## Warning: Removed 24 rows containing missing values (`geom_smooth()`).
```



6. Interpret the figure. What does it suggest with regards to the response of temperature to depth? Do the distribution of points suggest about anything about the linearity of this trend?

   Answer: The figure suggests that temperature decreases with depth, but it is not a simple linear relationship.

7. Perform a linear regression to test the relationship and display the results

```r
#7 linear regression of temp and depth
tempdepth_regression <-
  lm(NTL_LTER_July$temperature_C ~ NTL_LTER_July$depth)
summary(tempdepth_regression)
```

```
##
## Call:
## lm(formula = NTL_LTER_July$temperature_C ~ NTL_LTER_July$depth)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.5173 -3.0192  0.0633  2.9365 13.5834
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           21.95597    0.06792   323.3   <2e-16 ***
```

```
## NTL_LTER_July$depth -1.94621    0.01174  -165.8   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.835 on 9726 degrees of freedom
## Multiple R-squared:  0.7387, Adjusted R-squared:  0.7387
## F-statistic: 2.75e+04 on 1 and 9726 DF,  p-value: < 2.2e-16
```

8. Interpret your model results in words. Include how much of the variability in temperature is explained by changes in depth, the degrees of freedom on which this finding is based, and the statistical significance of the result. Also mention how much temperature is predicted to change for every 1m change in depth.

   Answer: 73.87% of the variability in temperature is explained by changes in depth, but it is not the only factor impacting temperature. This finding is based on 9726 degrees of freedom. Per meter of depth change, temperature change -1.95. Our findings are significant because the p value is p-value: < 2.2e-16.

Multiple regression

Let's tackle a similar question from a different approach. Here, we want to explore what might the best set of predictors for lake temperature in July across the monitoring period at the North Temperate Lakes LTER.

9. Run an AIC to determine what set of explanatory variables (year4, daynum, depth) is best suited to predict temperature.

10. Run a multiple regression on the recommended set of variables.

```r
#9 AIC to find what variables (year4, daynum, depth) are best suited to find temp
tempAIC <- lm(data = NTL_LTER_July, temperature_C ~ depth + year4 + daynum)
step(tempAIC) #choose a model by AIC in a Stepwise Algorithm
```

```
## Start:  AIC=26065.53
## temperature_C ~ depth + year4 + daynum
##
##          Df Sum of Sq    RSS   AIC
## <none>                141687 26066
## - year4   1       101 141788 26070
## - daynum  1      1237 142924 26148
## - depth   1    404475 546161 39189
```

```
##
## Call:
## lm(formula = temperature_C ~ depth + year4 + daynum, data = NTL_LTER_July)
##
## Coefficients:
## (Intercept)        depth        year4       daynum
##    -8.57556     -1.94644      0.01134      0.03978
```

```r
#10 multiple regression on the recommended set of variables
tempRegs <- lm(data = NTL_LTER_July,
                  temperature_C ~ depth + year4+ daynum)
summary(tempRegs)
```

```
##
## Call:
## lm(formula = temperature_C ~ depth + year4 + daynum, data = NTL_LTER_July)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.6536 -3.0000  0.0902  2.9658 13.6123
##
## Coefficients:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept) -8.575564   8.630715   -0.994  0.32044
## depth       -1.946437   0.011683 -166.611  < 2e-16 ***
## year4        0.011345   0.004299    2.639  0.00833 **
## daynum       0.039780   0.004317    9.215  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.817 on 9724 degrees of freedom
## Multiple R-squared:  0.7412, Adjusted R-squared:  0.7411
## F-statistic:  9283 on 3 and 9724 DF,  p-value: < 2.2e-16
```

11. What is the final set of explanatory variables that the AIC method suggests we use to predict temperature in our multiple regression? How much of the observed variance does this model explain? Is this an improvement over the model using only depth as the explanatory variable?

    Answer: We will use year4, daynum, depth as the explanatory variables because the AIC method showed that removing none of the three variables resulted in a stronger model than any one single variable. This model explains 74.12% of the observed variance. This is an improvement over the model using only depth, which explained 73.87%.

Analysis of Variance

12. Now we want to see whether the different lakes have, on average, different temperatures in the month of July. Run an ANOVA test to complete this analysis. (No need to test assumptions of normality or similar variances.) Create two sets of models: one expressed as an ANOVA models and another expressed as a linear model (as done in our lessons).

```r
#12
lake_diff <- NTL_LTER_July %>%
  group_by(lakename, year4, daynum, depth) %>%
  summarise(temperature_C)
```

```
## `summarise()` has grouped output by 'lakename', 'year4', 'daynum'. You can
## override using the `.groups` argument.
```

```r
summary(lake_diff)
```

```
##    lakename             year4          daynum          depth
##  Length:9728        Min.   :1984   Min.   :182.0   Min.   : 0.000
##  Class :character   1st Qu.:1992   1st Qu.:190.0   1st Qu.: 2.000
##  Mode  :character   Median :1998   Median :198.0   Median : 4.500
##                     Mean   :1999   Mean   :197.5   Mean   : 4.745
##                     3rd Qu.:2006   3rd Qu.:205.0   3rd Qu.: 7.000
##                     Max.   :2016   Max.   :213.0   Max.   :16.000
##  temperature_C
##  Min.   : 0.30
##  1st Qu.: 5.50
##  Median :10.10
##  Mean   :12.72
##  3rd Qu.:20.80
##  Max.   :34.10
```

```r
#model as anova
lake_diff_anova1 <- aov(data = lake_diff, temperature_C ~ lakename)
summary(lake_diff_anova1)
```

```
##               Df Sum Sq Mean Sq F value Pr(>F)
## lakename       8  21642  2705.2      50 <2e-16 ***
## Residuals   9719 525813    54.1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#model as lm
lake_diff_anova2 <- lm(data = lake_diff, temperature_C ~ lakename)
summary(lake_diff_anova2)
```

```
##
## Call:
## lm(formula = temperature_C ~ lakename, data = lake_diff)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -10.769  -6.614  -2.679   7.684  23.832
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 17.6664     0.6501  27.174  < 2e-16 ***
## lakenameCrampton Lake       -2.3145     0.7699  -3.006 0.002653 **
## lakenameEast Long Lake      -7.3987     0.6918 -10.695  < 2e-16 ***
## lakenameHummingbird Lake    -6.8931     0.9429  -7.311 2.87e-13 ***
## lakenamePaul Lake           -3.8522     0.6656  -5.788 7.36e-09 ***
## lakenamePeter Lake          -4.3501     0.6645  -6.547 6.17e-11 ***
## lakenameTuesday Lake        -6.5972     0.6769  -9.746  < 2e-16 ***
## lakenameWard Lake           -3.2078     0.9429  -3.402 0.000672 ***
## lakenameWest Long Lake      -6.0878     0.6895  -8.829  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 7.355 on 9719 degrees of freedom
## Multiple R-squared:  0.03953,    Adjusted R-squared:  0.03874
## F-statistic:    50 on 8 and 9719 DF,  p-value: < 2.2e-16
```

13. Is there a significant difference in mean temperature among the lakes? Report your findings.

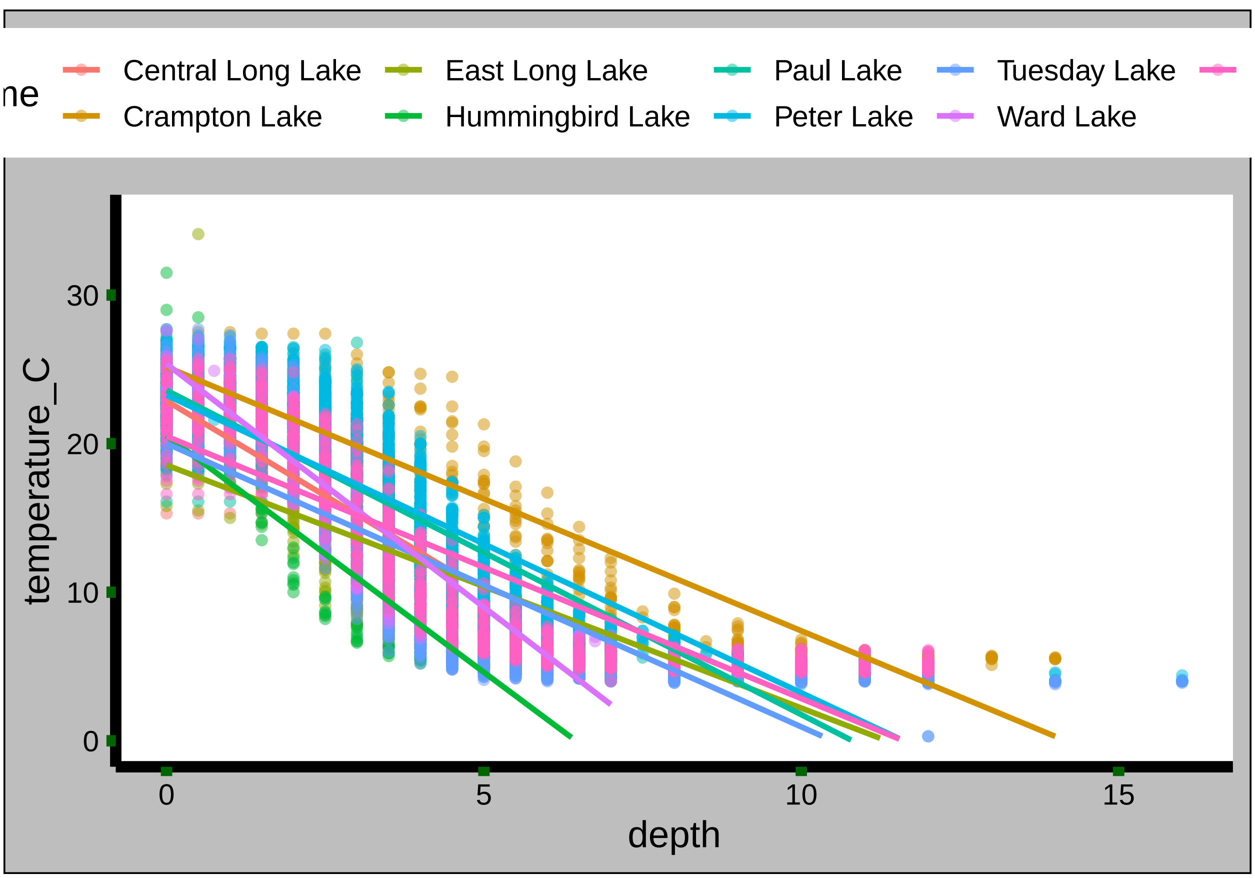
    Answer: The p-value is <2.2e-16, so there is significant evidence that there is a difference in mean temperature among the lakes.

14. Create a graph that depicts temperature by depth, with a separate color for each lake. Add a geom_smooth (method = "lm", se = FALSE) for each lake. Make your points 50 % transparent. Adjust your y axis limits to go from 0 to 35 degrees. Clean up your graph to make it pretty.

```
#14.
lake_diff_plot <- ggplot(lake_diff,
                         (aes(x = depth, y = temperature_C, color = lakename))) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", aes(x = depth, y = temperature_C), se = FALSE) +
  ylim(0, 35)
print(lake_diff_plot)
```

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

## Warning: Removed 73 rows containing missing values (`geom_smooth()`).
```



15. Use the Tukey's HSD test to determine which lakes have different means.

```r
#15
lakeHSD<- TukeyHSD(lake_diff_anova1)
lakeHSD_groups <- HSD.test(lake_diff_anova1, "lakename", group = TRUE)
lakeHSD_groups
```

```
## $statistics
##   MSerror   Df     Mean       CV
##   54.1016 9719 12.72087 57.82135
##
## $parameters
##    test   name.t ntr StudentizedRange alpha
##   Tukey lakename   9         4.387504  0.05
##
## $means
##                   temperature_C      std    r         se Min  Max    Q25   Q50
## Central Long Lake      17.66641 4.196292  128 0.6501298 8.9 26.8 14.400 18.40
## Crampton Lake          15.35189 7.244773  318 0.4124692 5.0 27.5  7.525 16.90
## East Long Lake         10.26767 6.766804  968 0.2364108 4.2 34.1  4.975  6.50
## Hummingbird Lake       10.77328 7.017845  116 0.6829298 4.0 31.5  5.200  7.00
## Paul Lake              13.81426 7.296928 2660 0.1426147 4.7 27.7  6.500 12.40
## Peter Lake             13.31626 7.669758 2872 0.1372501 4.0 27.0  5.600 11.40
## Tuesday Lake           11.06923 7.698687 1524 0.1884137 0.3 27.7  4.400  6.80
## Ward Lake              14.45862 7.409079  116 0.6829298 5.7 27.6  7.200 12.55
## West Long Lake         11.57865 6.980789 1026 0.2296314 4.0 25.7  5.400  8.00
##                      Q75
## Central Long Lake 21.000
## Crampton Lake     22.300
## East Long Lake    15.925
## Hummingbird Lake  15.625
## Paul Lake         21.400
## Peter Lake        21.500
## Tuesday Lake      19.400
## Ward Lake         23.200
## West Long Lake    18.800
##
## $comparison
## NULL
##
## $groups
##                   temperature_C groups
## Central Long Lake      17.66641      a
## Crampton Lake          15.35189     ab
## Ward Lake              14.45862     bc
## Paul Lake              13.81426      c
## Peter Lake             13.31626      c
## West Long Lake         11.57865      d
## Tuesday Lake           11.06923     de
## Hummingbird Lake       10.77328     de
## East Long Lake         10.26767      e
##
## attr(,"class")
## [1] "group"
```

16.From the findings above, which lakes have the same mean temperature, statistically speaking, as Peter Lake? Does any lake have a mean temperature that is statistically distinct from all the other lakes?

> Answer: Peter and Paul Lakes have the same mean temperature. No lake has a mean temperature that is statistically distinct from all other lakes.

17. If we were just looking at Peter Lake and Paul Lake. What's another test we might explore to see whether they have distinct mean temperatures?

> Answer: The two-sample T-test would allow us to compare the means between the two lakes.

18. Wrangle the July data to include only records for Crampton Lake and Ward Lake. Run the two-sample T-test on these data to determine whether their July temperature are same or different. What does the test say? Are the mean temperatures for the lakes equal? Does that match you answer for part 16?

```
lakediff_CrampWardLakes <- lake_diff %>%
  filter(lakename %in% c("Crampton Lake", "Ward Lake"))

lakes_twosample <- t.test(lakediff_CrampWardLakes$temperature_C ~ lakediff_CrampWardLakes$lakename)
lakes_twosample
```

```
##
##  Welch Two Sample t-test
##
## data:  lakediff_CrampWardLakes$temperature_C by lakediff_CrampWardLakes$lakename
## t = 1.1181, df = 200.37, p-value = 0.2649
## alternative hypothesis: true difference in means between group Crampton Lake and group Ward Lake is n
## 95 percent confidence interval:
##  -0.6821129  2.4686451
## sample estimates:
## mean in group Crampton Lake     mean in group Ward Lake
##                    15.35189                    14.45862
```

> Answer: The test says that the two means are statistically the same. The p value is 0.2649, so we cannot reject the null hypothesis that "the true difference in between between Lakes Crampton and Ward is equal to 0." This does match part 16, as Crampton and Ward Lakes are both in group b.