Assignment 7: GLMs week 2 (Linear Regression and beyond)

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OVERVIEW

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

Directions

1. Change "Student Name" on line 3 (above) with your name.
2. Work through the steps, **creating code and output** that fulfill each instruction.
3. Be sure to **answer the questions** in this assignment document.
4. When you have completed the assignment, **Knit** the text and code into a single PDF file.
5. After Knitting, submit the completed exercise (PDF file) to the dropbox in Sakai. Add your last name into the file name (e.g., "Salk_A06_GLMs_Week1.Rmd") prior to submission.

The completed exercise is due on Tuesday, February 25 at 1:00 pm.

Set up your session

1. Set up your session. Check your working directory, load the tidyverse, nlme, and piecewiseSEM packages, import the *raw* NTL-LTER raw data file for chemistry/physics, and import the processed litter dataset. You will not work with dates, so no need to format your date columns this time.

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

```
#----------------------------------------------------------------------------------------------------
#1: Loading Packages
pkgs = c(
  "tidyverse",
  "nlme",
  "piecewiseSEM"
)
i = pkgs[!pkgs %in% installed.packages()]
if(length(i) > 0)
  install.packages(i)
lapply(pkgs, library, character.only = TRUE)
```

```
## [[1]]
##  [1] "forcats"   "stringr"   "dplyr"     "purrr"     "readr"     "tidyr"
##  [7] "tibble"    "ggplot2"   "tidyverse" "stats"     "graphics"  "grDevices"
## [13] "utils"     "datasets"  "methods"   "base"
##
## [[2]]
##  [1] "nlme"      "forcats"   "stringr"   "dplyr"     "purrr"     "readr"
##  [7] "tidyr"     "tibble"    "ggplot2"   "tidyverse" "stats"     "graphics"
## [13] "grDevices" "utils"     "datasets"  "methods"   "base"
##
## [[3]]
##  [1] "piecewiseSEM" "nlme"         "forcats"      "stringr"      "dplyr"
##  [6] "purrr"        "readr"        "tidyr"        "tibble"       "ggplot2"
## [11] "tidyverse"    "stats"        "graphics"     "grDevices"    "utils"
## [16] "datasets"     "methods"      "base"
```

```
#1
getwd()
```

```
## [1] "C:/Users/krist/Box Sync/Spring 2020/R/Environmental_Data_Analytics_2020"
```

```
cpraw <- read.csv("./Data/Raw/NTL-LTER_Lake_ChemistryPhysics_Raw.csv")
litter <- read.csv("./Data/Processed/NEON_NIWO_Litter_mass_trap_Processed.csv")

#2
blahtheme <- theme_classic(base_size = 14) +
  theme(axis.text = element_text(color = "darkblue"), axis.ticks = element_line(colour = 'darkseagreen4
        legend.position = "bottom")

theme_set(blahtheme)
```

NTL-LTER test

Research question: What is the best set of predictors for lake temperatures in July across the monitoring period at the North Temperate Lakes LTER?

3. Wrangle your NTL-LTER dataset with a pipe function so that it contains only the following criteria:

- Only dates in July (hint: use the daynum column). No need to consider leap years.
- Only the columns: lakename, year4, daynum, depth, temperature_C
- Only complete cases (i.e., remove NAs)

4. Run an AIC to determine what set of explanatory variables (year4, daynum, depth) is best suited to predict temperature. Run a multiple regression on the recommended set of variables.

```
#3
cp <-
  cpraw %>%
  filter(daynum > 181 & daynum < 213)%>%
 select(lakename, year4, daynum, depth, temperature_C)%>%
   na.exclude()

#4
cpaic <- lm(data = cp, temperature_C ~ lakename + year4 +
              daynum + depth)
step(cpaic)
```

```
## Start:  AIC=24461.34
## temperature_C ~ lakename + year4 + daynum + depth
##
##            Df Sum of Sq    RSS   AIC
## <none>                  120062 24461
## - year4     1       184 120245 24474
## - daynum    1      1346 121407 24568
## - lakename  8     21056 141118 26016
## - depth     1    403139 523201 38770
```

```
##
## Call:
```

```
## lm(formula = temperature_C ~ lakename + year4 + daynum + depth,
##     data = cp)
##
## Coefficients:
##              (Intercept)     lakenameCrampton Lake    lakenameEast Long Lake
##                 45.17306                   4.71362                  -1.46041
## lakenameHummingbird Lake         lakenamePaul Lake        lakenamePeter Lake
##                 -4.73042                   0.99422                   1.44048
##     lakenameTuesday Lake         lakenameWard Lake    lakenameWest Long Lake
##                 -1.38445                  -0.46590                  -0.16847
##                    year4                    daynum                     depth
##                 -0.01588                   0.04157                  -1.96540
```

```
cpmodel <- lm(formula = temperature_C ~ lakename + year4 + daynum + depth,
    data = cp)
summary(cpmodel)
```

```
##
## Call:
## lm(formula = temperature_C ~ lakename + year4 + daynum + depth,
##     data = cp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.8938 -3.0274 -0.2114  2.7781 15.2926
##
## Coefficients:
##                           Estimate Std. Error  t value Pr(>|t|)
## (Intercept)              45.173063   8.248578    5.476 4.45e-08 ***
## lakenameCrampton Lake     4.713617   0.382185   12.333  < 2e-16 ***
## lakenameEast Long Lake   -1.460406   0.343271   -4.254 2.12e-05 ***
## lakenameHummingbird Lake -4.730421   0.459795  -10.288  < 2e-16 ***
## lakenamePaul Lake         0.994222   0.331643    2.998 0.002726 **
## lakenamePeter Lake        1.440479   0.331406    4.347 1.40e-05 ***
## lakenameTuesday Lake     -1.384450   0.336476   -4.115 3.91e-05 ***
## lakenameWard Lake        -0.465900   0.464619   -1.003 0.316003
## lakenameWest Long Lake   -0.168474   0.341961   -0.493 0.622257
## year4                    -0.015885   0.004118   -3.857 0.000115 ***
## daynum                    0.041574   0.003985   10.432  < 2e-16 ***
## depth                    -1.965403   0.010885 -180.566  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.516 on 9710 degrees of freedom
## Multiple R-squared:  0.7803, Adjusted R-squared:   0.78
## F-statistic:  3135 on 11 and 9710 DF,  p-value: < 2.2e-16
```

5. What is the final set of explanatory variables that predict temperature from your multiple regression? How much of the observed variance does this model explain?

   Answer: Wow. The model explains 78% of the variance. That's crazy high! Final set of explanatory variables that predict temp: lakes (crampton lake, east long lake, hummingbird lake, paul lake, peter lake, tuesday lake, ward lake, and long lake), year, day within July, and depth. The only lake that didn't have a specific coefficient listed was Central Long Lake.

6. Run an interaction effects ANCOVA to predict temperature based on depth and lakename from the

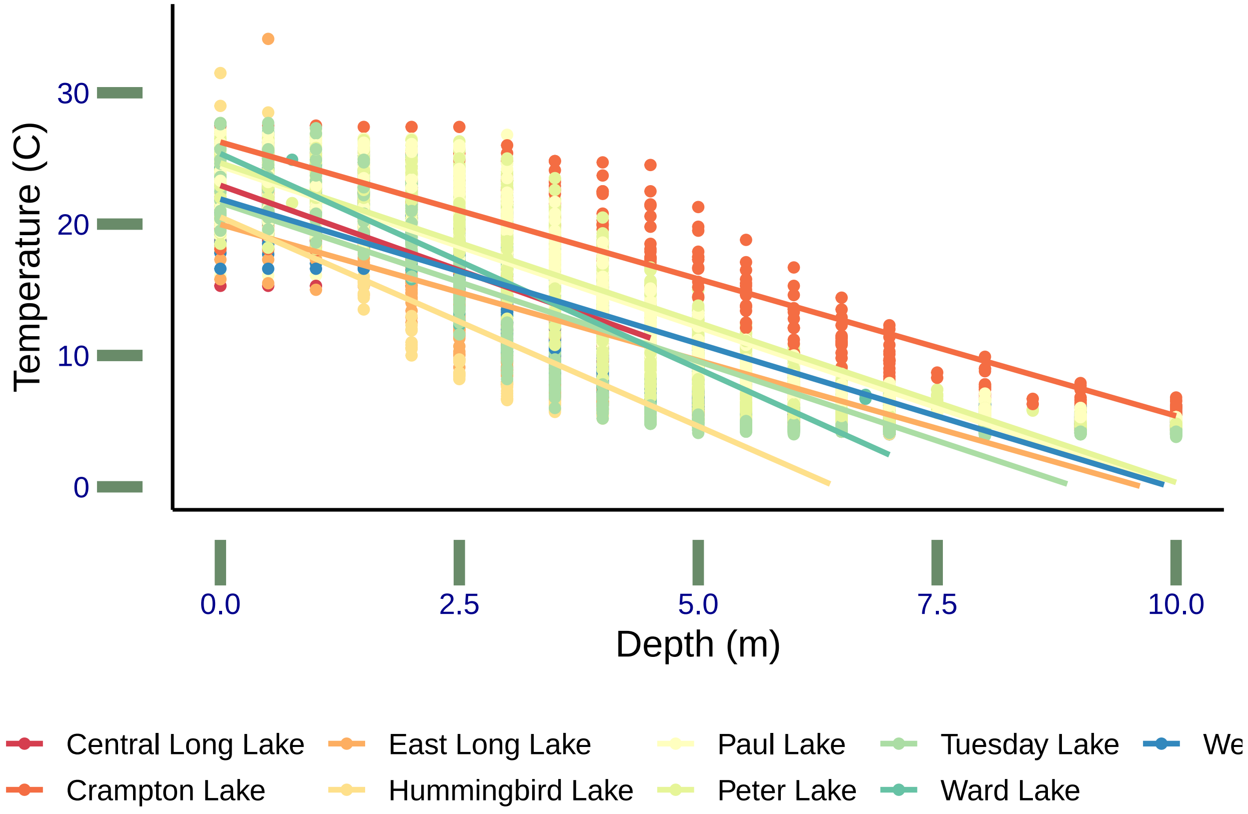
same wrangled dataset.

```
##
## Call:
## lm(formula = temperature_C ~ lakename * depth, data = cp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.6455 -2.9133 -0.2879  2.7567 16.3606
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    22.9455     0.5861  39.147  < 2e-16 ***
## lakenameCrampton Lake           2.2173     0.6804   3.259  0.00112 **
## lakenameEast Long Lake         -4.3884     0.6191  -7.089 1.45e-12 ***
## lakenameHummingbird Lake       -2.4126     0.8379  -2.879  0.00399 **
## lakenamePaul Lake               0.6105     0.5983   1.020  0.30754
## lakenamePeter Lake              0.2998     0.5970   0.502  0.61552
## lakenameTuesday Lake           -2.8932     0.6060  -4.774 1.83e-06 ***
## lakenameWard Lake               2.4180     0.8434   2.867  0.00415 **
## lakenameWest Long Lake         -2.4663     0.6168  -3.999 6.42e-05 ***
## depth                          -2.5820     0.2411 -10.711  < 2e-16 ***
## lakenameCrampton Lake:depth     0.8058     0.2465   3.268  0.00109 **
## lakenameEast Long Lake:depth    0.9465     0.2433   3.891  0.00010 ***
## lakenameHummingbird Lake:depth -0.6026     0.2919  -2.064  0.03903 *
## lakenamePaul Lake:depth         0.4022     0.2421   1.662  0.09664 .
## lakenamePeter Lake:depth        0.5799     0.2418   2.398  0.01649 *
## lakenameTuesday Lake:depth      0.6605     0.2426   2.723  0.00648 **
## lakenameWard Lake:depth        -0.6930     0.2862  -2.421  0.01548 *
## lakenameWest Long Lake:depth    0.8154     0.2431   3.354  0.00080 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.471 on 9704 degrees of freedom
## Multiple R-squared:  0.7861, Adjusted R-squared:  0.7857
## F-statistic:  2097 on 17 and 9704 DF,  p-value: < 2.2e-16
```

7. Is there a significant interaction between depth and lakename? How much variance in the temperature observations does this explain?

   Answer: There is a significant interaction between depth and lakename, with an overall model p-value < 0.0001. The adjusted R2 value is 0.79, which is even higher than the other lm! The interactions between depth and individual lakes have varied p-values, with Hummingird being the only one without significant interaction with depth (p-values > 0.05). I suppose all this suggests that site specific conditions include total depth, so there's an interaction.

8. 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.



9. Run a mixed effects model to predict dry mass of litter. We already know that nlcdClass and functionalGroup have a significant interaction, so we will specify those two variables as fixed effects with an interaction. We also know that litter mass varies across plot ID, but we are less interested in the actual effect of the plot itself but rather in accounting for the variance among plots. Plot ID will be our random effect.

a. Build and run a mixed effects model.
b. Check the difference between the marginal and conditional R2 of the model.

```
##   Response   family     link method  Marginal Conditional
## 1  dryMass gaussian identity   none 0.2465822   0.2679023
```

b. continued… How much more variance is explained by adding the random effect to the model?

Answer: approximately 2 %, with marginal r2 = 0.24 and conditional = 0.26.

c. Run the same model without the random effect.
d. Run an anova on the two tests.

```
##   Response   family     link method R.squared
## 1  dryMass gaussian identity   none 0.2515836
```

```
##              Model df      AIC      BIC    logLik   Test  L.Ratio p-value
## litter.mixed     1 26 9038.575 9179.479 -4493.287
## litter.fixed     2 25 9058.088 9193.573 -4504.044 1 vs 2 21.51338  <.0001
```

d. continued… Is the mixed effects model a better model than the fixed effects model? How do you know?

Answer: The fixed effect is slightly better than the mixed effect because the AIC is slightly lower (mixed = 9038.6; fixed = 9038.1).