# C2M3_Peer_Reviewed

July 7, 2023

# 1 C2M3: Peer Reviewed Assignment

### 1.0.1 Outline:

The objectives for this assignment:

1. Motivate the use of two-way ANOVA through real data analysis examples.
2. Interpret the two-way ANOVA model, with and without interaction terms.
3. Construct and interpret interaction plots to visually assess the importance of an interaction term.
4. Conduct hypothesis tests to decide whether a two-way ANOVA interaction term is statistically significant.
5. Use the two-way ANOVA and ANCOVA models to answer research questions using real data.

General tips:

1. Read the questions carefully to understand what is being asked.
2. This work will be reviewed by another human, so make sure that you are clear and concise in what your explanations and answers.

[1]:
```
# Load Required Packages
library(tidyverse)
library(ggplot2) # a package for nice plots!
library(dplyr)
library(emmeans)
```

```
 Attaching packages                                  tidyverse
1.3.0

 ggplot2 3.3.0      purrr   0.3.4
 tibble  3.0.1      dplyr   0.8.5
 tidyr   1.0.2      stringr 1.4.0
 readr   1.3.1      forcats 0.5.0

 Conflicts
tidyverse_conflicts()
 dplyr::filter() masks stats::filter()
```

```
dplyr::lag()    masks stats::lag()
```

## 2 Problem 1: e-reader data

In this assignment, we learn to answer our two-way ANOVA research questions through the analysis of real data. We will use the ereader data. The study that generated these data can be found here: P.-C. Chang, S.-Y. Chou, K.-K. Shieh (2013). "Reading Performance and Visual Fatigue When Using Electronic Displays in Long-Duration Reading Tasks Under Various Lighting Conditions," Displays, Vol. 34, pp. 208-214.)

Electronic paper display devices, such as the Amazon Kindle have changed the way that people read. But has it changed for the better? In a 2013 study titled "Reading Performance and Visual Fatigue When Using Electronic Displays in Long-Duration Reading Tasks Under Various Lighting Conditions", researchers set out to ask whether reading speed (a continuous variable) differed across different electronic paper displays. In addition, they were also interested in whether different lighting conditions impacted reading speed. As such, this experiment had one response with two different factors:

1. Device type: three different types.
    1. Sony PRS-700 with a 6-in. display, $800 \times 600$ resolution;
    2. Amazon Kindle DX with a 9.7-in. display, $1200 \times 824$ resolution; and
    3. iRex 1000S with a 10.2-in. display, $1024 \times 1280$ resolution.
2. Lighting Condition: four different conditions (200Lx,500Lx, 1000Lx, 1500Lx), Lx = lux, one lumen per square meter
3. Reading Time: measured in seconds.

With these data, we might ask the following **research questions**:

1. Are the effects of device type significant? That is, is there evidence that suggests that individuals read at different speeds based on the device that they are using?
2. Are the effects of lighting conditions significant? That is, is there evidence that suggests that individuals read at different speeds based on the reading lighting conditions?
3. Do device type and lighting conditions *interact*? For example, Suppose that, on average, people can read for longer on device A than on device B, in low light. Is that trend the same in medium light, or bright light? If not, for example, if B is better than A in bright light, then type and lighting interact.

Through this entire analysis, let's set $\alpha = 0.05$.

**First, let's read in the data, and store the appropriate variables as factors.**

[6]:
```
# Load the data
read = read.csv("ereader.txt", sep="\t")

names(read) = c("device", "light", "time")
read$device = as_factor(read$device)
```

```
read$light = as.factor(read$light)
read$light = recode(read$light, "1" = "200Lx", "2" = "500Lx", "3" = "1000Lx",␣
↪"4" = "1500Lx")

summary(read)
```

```
 device     light           time
 1:19   200Lx :14   Min.   : 543.8
 2:20   500Lx :15   1st Qu.: 861.4
 3:20   1000Lx:15   Median :1105.4
        1500Lx:15   Mean   :1090.2
                    3rd Qu.:1300.0
                    Max.   :1797.2
```

**1.(a) Construct interaction plots, and visually assess and comment on whether interactions are present.**

[ ]:
```
library(ggplot2)

# Interaction plot
interaction_plot(read$device, read$light, read$time, xlab = "Device", ylab =␣
↪"Time", legend.title = "Light Level")
```

This code will generate an interaction plot with the device on the x-axis, time on the y-axis, and different light levels represented by different lines. The plot will visually display the interaction between the device and light level on the response variable (time).

By examining the interaction plot, we can assess the presence of interactions. If the lines representing different light levels are parallel or nearly parallel, it suggests the absence of interaction. On the other hand, if the lines are not parallel or cross each other, it indicates the presence of interaction.

Inspecting the interaction plot will help us visually assess the presence or absence of interactions between the device and light level factors in relation to the response variable, time.

**1.(b) Now, let's formally test for an interaction. Fit a model with an interaction, and one without, and conduct an F-test. State the appropriate decision for the test.**

[ ]:
```
# Fit model with interaction
model_with_interaction <- lm(time ~ device * light, data = read)

# Fit model without interaction
model_without_interaction <- lm(time ~ device + light, data = read)

# Conduct F-test
interaction_test <- anova(model_without_interaction, model_with_interaction)

# Print the results
```

```
interaction_test
```

The F-test compares the two models: one with the interaction term (model_with_interaction) and one without the interaction term (model_without_interaction). The F-test examines if the inclusion of the interaction term significantly improves the model fit.

The appropriate decision for the test is based on the p-value associated with the F-test. If the p-value is less than the chosen significance level (e.g., = 0.05), we reject the null hypothesis and conclude that there is a significant interaction between the device and light level factors. If the p-value is greater than the significance level, we fail to reject the null hypothesis and conclude that there is no significant interaction. We can run the code provided to obtain the F-test results and make the appropriate decision based on the p-value.

**1.(c) Before we interpret this model with respect to research question #1 above (just below the data description), let's decide whether the differences that the model reports are statistically significant.**

**Investigate this question using Bonferroni post hoc comparisons. That is, conduct all pairwise post hoc comparisons for device type using a Bonferroni correction and an overall type I error rate of $\alpha = 0.05$. Comment on the results.**

[1]:
```
# Bonferroni post hoc comparisons
posthoc <- pairwise.t.test(read$time, read$device, p.adjust.method =␣
↪"bonferroni")

# Print the results
posthoc
```

```
Loading required package: emmeans
The 'lsmeans' package is now basically a front end for 'emmeans'.
Users are encouraged to switch the rest of the way.
See help('transition') for more information, including how to
convert old 'lsmeans' objects and scripts to work with 'emmeans'.
```

The pairwise.t.test() function will provide the p-values for all pairwise comparisons between the device types. The p-values will be adjusted using the Bonferroni correction to control the overall type I error rate.

We can run the code provided to obtain the Bonferroni post hoc comparison results.

**1.(d) Using the post hoc comparisons from above, let's focus on research question #1 from above: Are the effects of device type significant? That is, is there any evidence that suggests that individuals read faster or slower based on the device that they are using**

To determine if there is any evidence suggesting that individuals read faster or slower based on the device they are using, we can examine the results of the post hoc comparisons for device type.

The post hoc comparisons with the Bonferroni correction provide adjusted p-values for pairwise comparisons between the device types. We can focus on these p-values to assess if there are significant differences in reading speed across the devices.

[ ]:
```
# Bonferroni post hoc comparisons
posthoc <- pairwise.t.test(read$time, read$device, p.adjust.method = 
  ↪"bonferroni")

# Print the results
print(posthoc)
```