C2M3_Peer_Reviewed

July 2, 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.

[6]:
```
# Load Required Packages
library(tidyverse)
library(ggplot2) # a package for nice plots!
library(dplyr)
library(emmeans)
```

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, 800×600 resolution;
    2. Amazon Kindle DX with a 9.7-in. display, 1200×824 resolution; and
    3. iRex 1000S with a 10.2-in. display, 1024×1280 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 $\alpha = 0.05$.

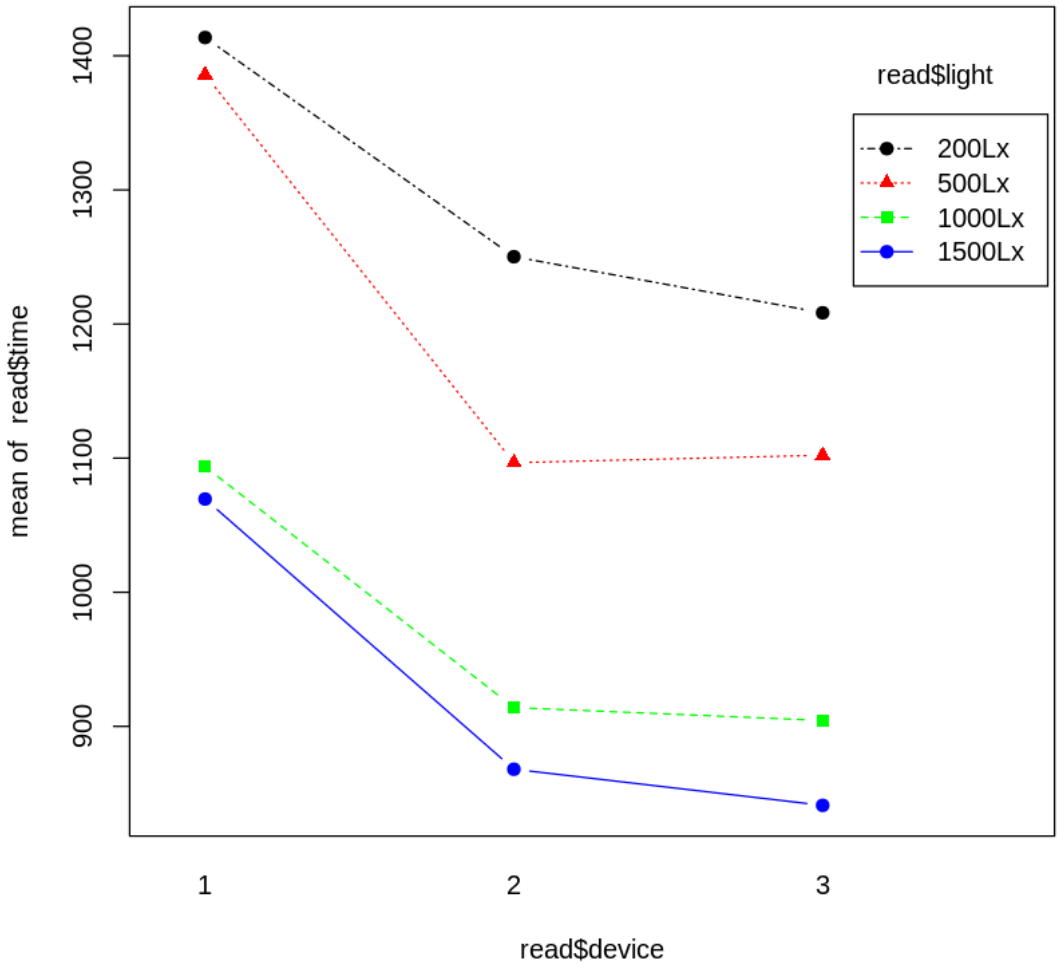
First, let's read in the data, and store the appropriate variables as factors.

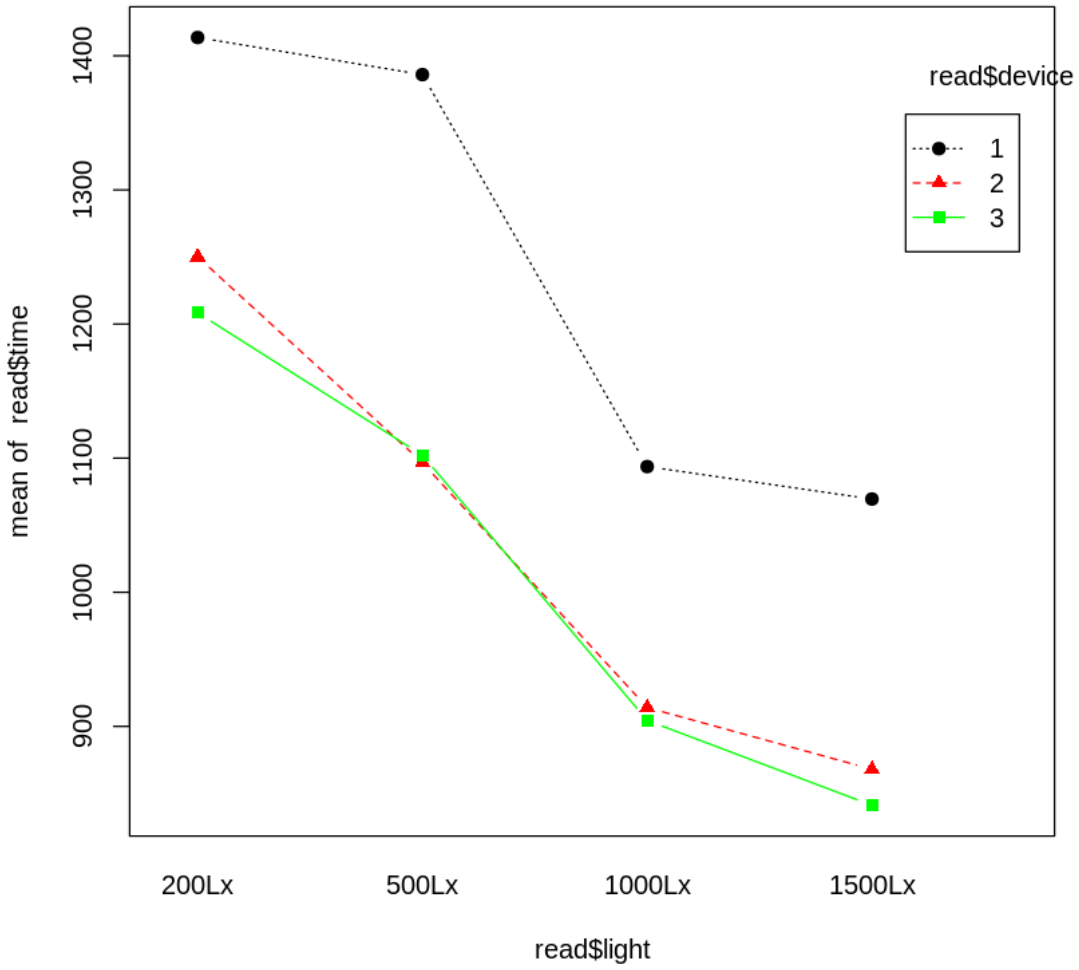
[7]:
```
# Load the data
read = read.csv("ereader.txt", sep="\t")

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.

[17]:
```
interaction.plot(x.factor     = read$device,
                 trace.factor = read$light,
                 response     = read$time,
                 fun = mean,
                 type="b",
                 col=c("black","red","green","blue"),  ### Colors for levels of␣
 ↪trace var.
                 pch=c(19, 17, 15),             ### Symbols for levels of trace␣
 ↪var.
                 fixed=TRUE,                    ### Order by factor order in␣
 ↪data
                 leg.bty = "o")

interaction.plot(x.factor     = read$light,
                 trace.factor = read$device,
                 response     = read$time,
                 fun = mean,
                 type="b",
                 col=c("black","red","green","blue"),  ### Colors for levels of␣
 ↪trace var.
                 pch=c(19, 17, 15),             ### Symbols for levels of trace␣
 ↪var.
                 fixed=TRUE,                    ### Order by factor order in␣
 ↪data
                 leg.bty = "o")
```


mean of read$time
1400
1300
1200
1100
1000
900
read$light
200Lx
500Lx
1000Lx
1500Lx
1
2
3
read$device



When plotting the divice Vs Time grouped by light, the plot showed ther are not interaction as the plots for each group is almost parallel. In the second graph it coudl be an interaccion bewteen the divice 2 and 3 as showed in the plot.

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.

[8]:
```
mod=lm(time~device+light,data=read)
mod_interac=lm(time~device+light+device:light,data=read)
anova(mod,mod_interac)
```

A anova: 2 × 6

	Res.Df <dbl>	RSS <dbl>	Df <dbl>	Sum of Sq <dbl>	F <dbl>	Pr(>F) <dbl>
1	53	3628970	NA	NA	NA	NA
2	47	3603108	6	25861.55	0.05622427	0.9992146

- Ho: The recuced model is sufficient
- H1: The reduce model in not sufficient

The p-value is greater than 0.05, so we cannot reject the null, and work with the reduce model without interaction.

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.

[10]:
```
# Your Code Here

pairs(lsmeans(mod, "device", adjust="bonferroni"))

pairs(lsmeans(mod, "light", adjust="bonferroni"))
```

```
 contrast estimate   SE df t.ratio p.value
 1 - 2       209.7 83.9 53 2.500   0.0405
 1 - 3       227.9 83.9 53 2.717   0.0237
 2 - 3        18.2 82.7 53 0.220   0.9737

Results are averaged over the levels of: light
P value adjustment: tukey method for comparing a family of 3 estimates


 contrast        estimate   SE df t.ratio p.value
 200Lx - 500Lx       97.5 97.3 53 1.002   0.7491
 200Lx - 1000Lx     321.7 97.3 53 3.306   0.0090
 200Lx - 1500Lx     366.2 97.3 53 3.763   0.0023
 500Lx - 1000Lx     224.2 95.5 53 2.346   0.1005
 500Lx - 1500Lx     268.7 95.5 53 2.812   0.0337
 1000Lx - 1500Lx     44.5 95.5 53 0.466   0.9662

Results are averaged over the levels of: device
P value adjustment: tukey method for comparing a family of 4 estimates
```

The p-value for the pairwaise for the 2-3 divice comparation allow us to conclude there is not statistical difference, this coincide with the graph for interaction as these two diveces almost have the same line.

the estimate for this pair will be not need for the model.

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

The difference exist when an individual uses the type 1 device for reading as the pairwaise comparation showed, in this case there is not difference for the device 2 and 3.

[ ]:
```
# Your Code Here
```