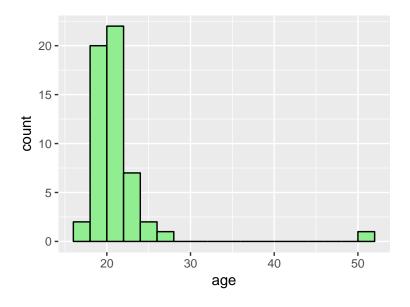
Information about the participants in the cartogram experiment

Demographics

Age distribution



Gender

Gender	Frequency
Female	37
Male	18

Highest level of education

Education	Frequency
High school	19
Some college	22
Bachelor's	1
Bachelor's	12
Master's	1

Information about prior knowledge

Familiarity with interactive computer graphics

Familiarity	Frequency
Very unfamiliar	0
Unfamiliar	12
Somewhat familiar	29
Familiar	14
Very familiar	0

Familiarity with cartograms

Familiarity	Frequency
Very unfamiliar	12
Unfamiliar	0
Somewhat familiar	17
Familiar	4
Very familiar	0
No response	22

Map affinity

On a world map, would you be able to point at the location where you were born?

Answer	Frequency
Yes, with confidence	39
Yes, with a little effort	10
Yes, with much effort	2
Possibly, but I'm uncertain	3
No	1

When you encounter the names of unfamiliar locations (e.g. countries, islands, lakes), how frequently do you immediately look them up on a map to find out where they are?

Answer	Frequency
Never	2
Rarely	15
Sometimes	19
Generally	16
Always	3

Colour vision

We showed six Ishihara plates to each participant. Participants 28, 37, 42, 50 responded differently from the majority in exactly one case each. Participant 2 had two, participant 34 even three abnormal responses. We should investigate whether participants 2 and 34 showed unusual responses to the remaining questions too.

Questions

Taxon (Task Taxonomy According to Nusrat & Kobourov 2015)

• CL - cluster: find the region that has the most similar data to a given region.

Sample Question: On the other monitor, you can see a conventional map of Brazil (left) and a cattle population cartogram (right). Out of the states listed below, which has a cattle population most similar to Mato Grosso do Sul (MS)? A. Rondonia (RO), B. Para (PA), C. Mato Grosso (MT), D. San Paulo (SP)

• CO - compare: compare data between two regions.

Sample Question: On the other monitor, you can see a conventional map of Germany (left) and a GDP cartogram (right). Is the GDP of Mecklenburg-Vorpommern (MV) higher than, approximately equal to or lower than the GDP of Rheinland-Pfalz (RP)? A. Higher, B. Approximately equal, C. Lower

DC - detect change: compare areas of a given region in two cartograms.

Sample Question: On the other monitor, you can see a conventional map of Brazil (left), a cattle population cartogram and a human population (right). You may have to use the cartogram selector tab to view both cartograms. Is the area of Amazonas (AM) in the cattle population cartogram higher than, approximately equal to or lower than its area in the human population cartogram? A. Higher, B. Approximately equal, C. Lower

• FA - find adjacency: find all neighbours of a given region.

Sample Question: On the other monitor, you can see a conventional map of Brazil (left) and a population cartogram (right). Which states are neighbours of the state highlighted in red in the population cartogram below? There may be more than one correct answer. A. Bahia (BA), B. Minals Gerals (MG), C. Maranhao (MA), D. Sergipe (SE)

• FL - filter: find all regions whose data surpasses that of a given region.

Sample Question: On the other monitor, you can see a conventional map of Germany (left) and a population cartogram (right). Out of the states listed below, which one(s) have a population higher than Baden-Wuerttemberg (BW)? There may be more than one correct answer. A. Nordrhein-Westfalen (NW), B. Hessen (HE), C. Niedersachen (NI), D. Bayern (BY).

• FT - find top: find the region that has the highest data across the country.

Sample Question: On the other monitor, you can see a conventional map of the USA (left) and a crop production cartogram (right). Which state of the USA has the highest crop production? A. California (CA), B. Montana (MT), C. Maine (ME), D. Iowa (IA).

• RE - recognize: identify the name of a given region highlighted in the cartogram.

Sample Question: On the other monitor, you can see a conventional map of the India (left) and a population cartogram (right). Which is the name of the state highlighted in the population cartogram? A. Haryana (HR), B. Punjab (PB), C. Rajasthan (RJ), D. Himachal Pradesh (HP).

• SU - summarize: compare data of three different regions in two cartograms.

Sample Question: On the other monitor, you can see a conventional map of Germany (left) and population cartograms for the years 1985 and 2015 (right). You may have to use the cartogram selector tab to view both cartograms. Three different regions are highlighted in yellow, purple and pink. What can you say about the change in population for each region from 1985 to 2015? For all three regions, A. Growth, B. Approximately No Change, C. Shrinking.

Treatment Groups

A - all (i.e. highlighting, infotip and switch button),

H - highlighting,

I - infotip,

N - none,

S - switch button.

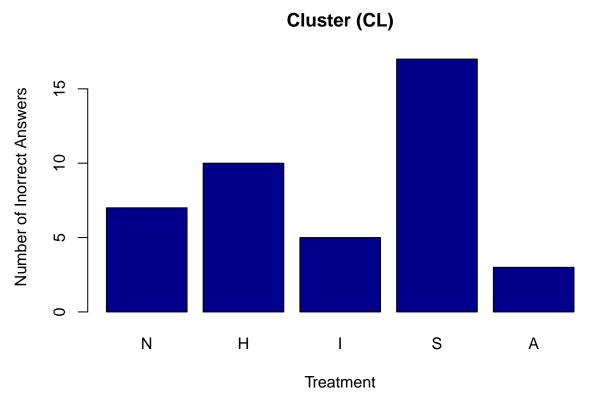
Correctness

A question is considered to be answered correctly if and only if all correct answers and no incorrect answers are selected. A question is considered to be answered incorrectly otherwise. There is no partial credit given for any question.

Results

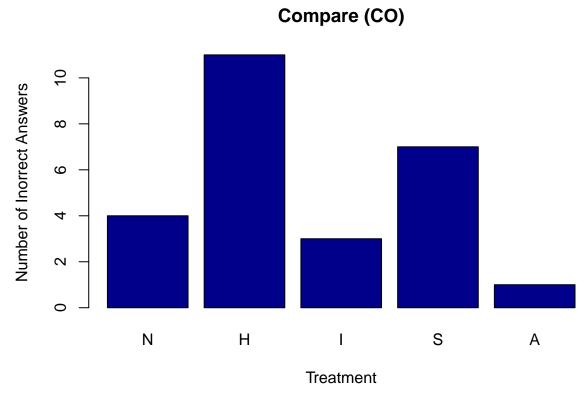
Histograms of the number of Incorrect Answers

 \mathbf{CL}



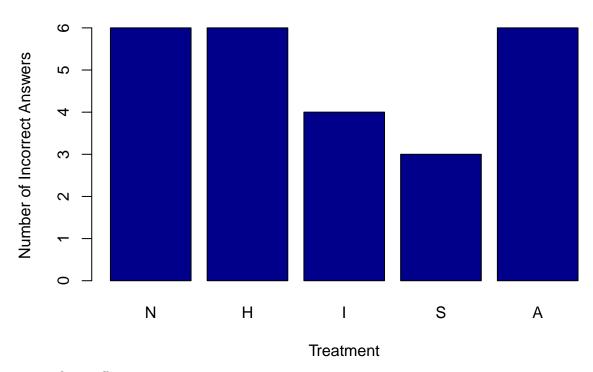
6 out of the 15 participants (one data point missing) who are provided with switch actually used switch.

 \mathbf{CO}



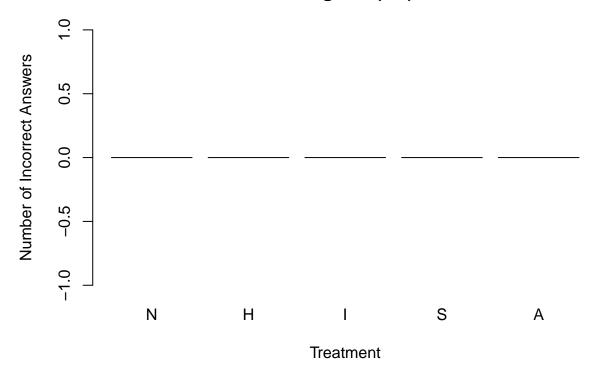
 \mathbf{DC}

Detect Change (DC)



 \mathbf{RE}

Recognize (RE)



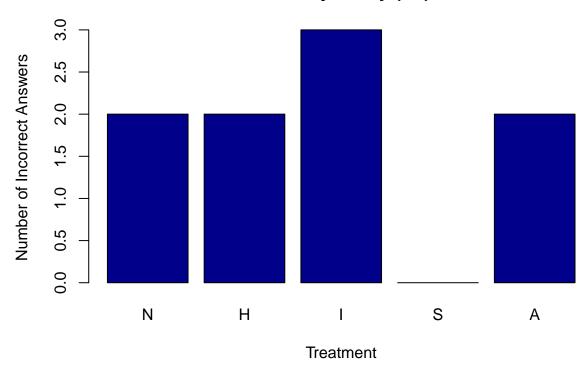
 \mathbf{SU}

Number of Incorrect Answers Number of Incorrect Answers N H I S A Treatment

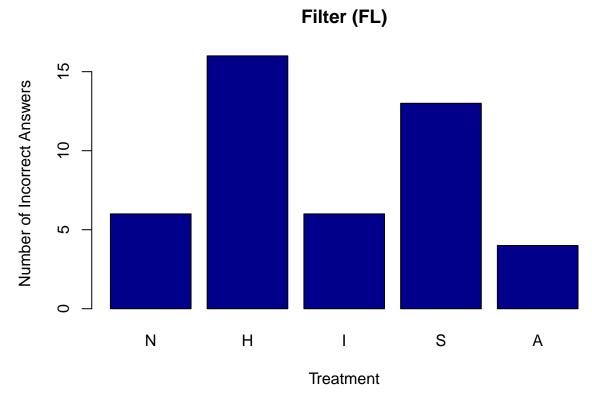
18 out of 18 participants who are provided with switch actually used switch.

 $\mathbf{F}\mathbf{A}$

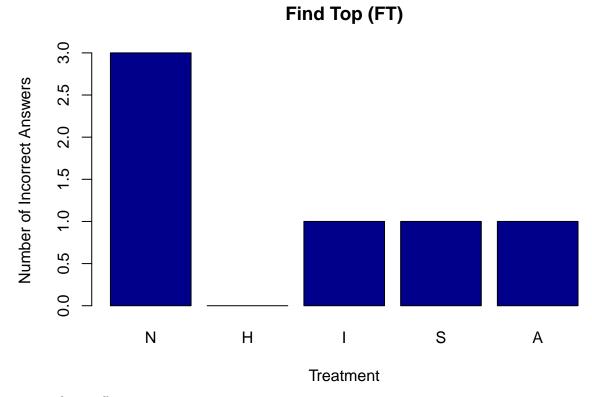
Find Adjacency (FA)



 \mathbf{FL}



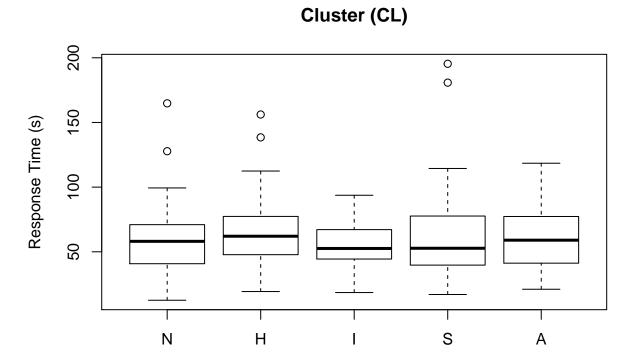
 \mathbf{FT}



no significant effects

Boxplots of Response Time Conditioned on Correctness

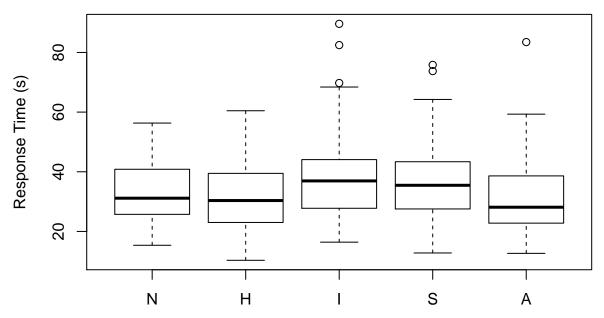
 \mathbf{CL}



nothing significant

 \mathbf{CO}

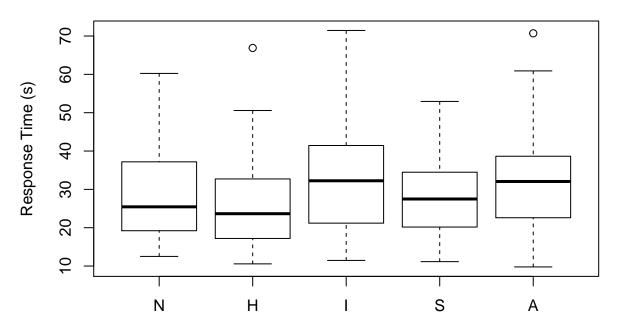




H does not help answer correctly, but the correct answer is quicker.

 \mathbf{DC}

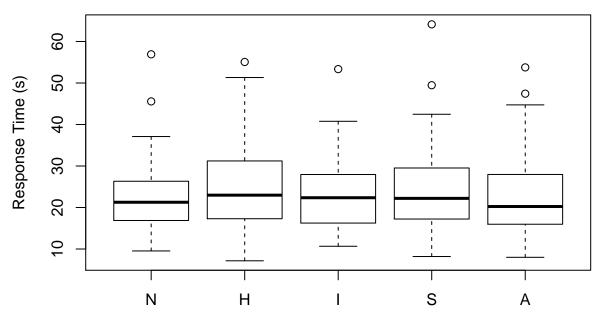
Detect Change (DC)



most participants use switch several times back and forth before choosing their answers

FA

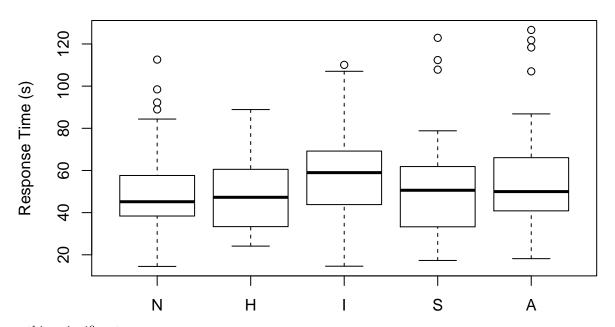
Find Adjacency (FA)



nothing significant

 \mathbf{FL}

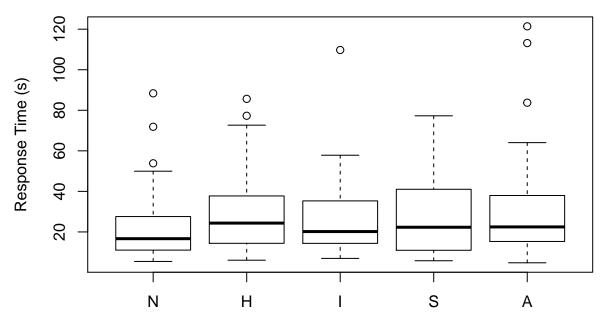
Filter (FL)



nothing significant

 \mathbf{FT}

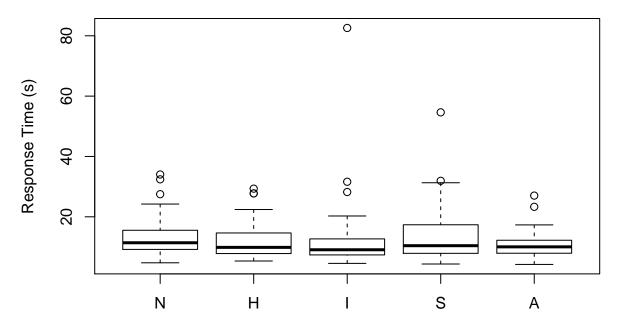
Find Top (FT)



nothing significant

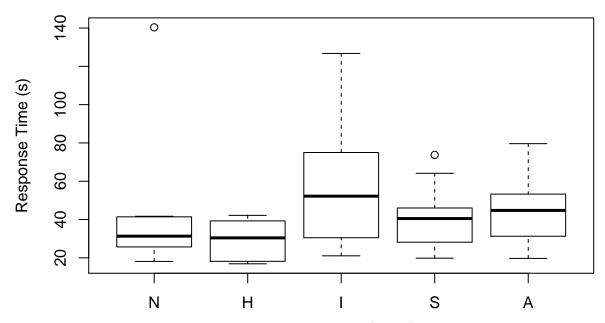
 \mathbf{RE}

Recognize (RE)



nothing significant

Summarize (SU)



the spread is significantly higher for I because of two outliers (>100s).

Experiments

Pairwise Prop Test

```
taxonomy <- rep(c("CL", "CO", "DC", "RE", "SU", "FA", "FL", "FT"))
for (i in 1:8) {
  print(taxonomy[i])
  ppt_matrix = response %>% select(treatment, taxon, is_correct)
  ppt_matrix_incorrect = filter(ppt_matrix, taxon == taxonomy[i], is_correct == FALSE)
  ppt_matrix_incorrect = select(ppt_matrix_incorrect, treatment)
  print(pairwise.prop.test(
   c(nrow(filter(ppt_matrix_incorrect, treatment == "N")),
     nrow(filter(ppt_matrix_incorrect, treatment == "H")),
     nrow(filter(ppt_matrix_incorrect, treatment == "I")),
     nrow(filter(ppt_matrix_incorrect, treatment == "S")),
     nrow(filter(ppt_matrix_incorrect, treatment == "A"))),
  rep(55, 5)))
}
## [1] "CL"
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
##
   Pairwise comparisons using Pairwise comparison of proportions
##
```

```
## data: c(nrow(filter(ppt_matrix_incorrect, treatment == "N")), nrow(filter(ppt_matrix_incorrect, ou
##
##
     1
           2
                 3
                       4
## 2 1.000 -
## 3 1.000 1.000 -
## 4 0.302 1.000 0.079 -
## 5 1.000 0.535 1.000 0.013
## P value adjustment method: holm
## [1] "CO"
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Pairwise comparisons using Pairwise comparison of proportions
## data: c(nrow(filter(ppt_matrix_incorrect, treatment == "N")), nrow(filter(ppt_matrix_incorrect, ou
##
##
           2
                 3
     1
## 2 0.669 -
## 3 1.000 0.407 -
## 4 1.000 1.000 1.000 -
## 5 1.000 0.059 1.000 0.531
## P value adjustment method: holm
## [1] "DC"
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
##
   Pairwise comparisons using Pairwise comparison of proportions
## data: c(nrow(filter(ppt_matrix_incorrect, treatment == "N")), nrow(filter(ppt_matrix_incorrect, ou
##
##
    1 2 3 4
```

```
## 2 1 - - -
## 3 1 1 - -
## 4 1 1 1 -
## 5 1 1 1 1
## P value adjustment method: holm
## [1] "RE"
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Pairwise comparisons using Pairwise comparison of proportions
##
## data: c(nrow(filter(ppt_matrix_incorrect, treatment == "N")), nrow(filter(ppt_matrix_incorrect, ou
##
##
   1 2 3 4
## 2 - - - -
## 3 - - - -
## 4 - - - -
## 5 - - - -
##
## P value adjustment method: holm
## [1] "SU"
##
## Pairwise comparisons using Pairwise comparison of proportions
## data: c(nrow(filter(ppt_matrix_incorrect, treatment == "N")), nrow(filter(ppt_matrix_incorrect, ou
```

```
##
##
                     3
                             4
    1
             2
## 2 1.00000 -
## 3 1.00000 1.00000 -
## 4 7.0e-06 9.6e-05 9.6e-05 -
## 5 9.6e-05 0.00081 0.00081 1.00000
## P value adjustment method: holm
## [1] "FA"
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
##
  Pairwise comparisons using Pairwise comparison of proportions
## data: c(nrow(filter(ppt_matrix_incorrect, treatment == "N")), nrow(filter(ppt_matrix_incorrect, ou
##
##
   1 2 3 4
## 2 1 - - -
## 3 1 1 - -
## 4 1 1 1 -
## 5 1 1 1 1
## P value adjustment method: holm
## [1] "FL"
##
## Pairwise comparisons using Pairwise comparison of proportions
```

```
## data: c(nrow(filter(ppt_matrix_incorrect, treatment == "N")), nrow(filter(ppt_matrix_incorrect, ou
##
##
     1
           2
                 3
                       4
## 2 0.287 -
## 3 1.000 0.287 -
## 4 0.781 1.000 0.781 -
## 5 1.000 0.065 1.000 0.287
## P value adjustment method: holm
## [1] "FT"
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
## Warning in prop.test(x[c(i, j)], n[c(i, j)], ...): Chi-squared
## approximation may be incorrect
##
## Pairwise comparisons using Pairwise comparison of proportions
## data: c(nrow(filter(ppt_matrix_incorrect, treatment == "N")), nrow(filter(ppt_matrix_incorrect, ou
##
##
    1 2 3 4
## 2 1 - - -
## 3 1 1 - -
## 4 1 1 1 -
## 5 1 1 1 1
## P value adjustment method: holm
```

ANOVA

```
taxonomy <- rep(c("CL", "CO", "DC", "RE", "SU", "FA", "FL", "FT"))
for (i in 1:8) {
 print(taxonomy[i])
  anova matrix = response %>% select(response time, treatment, taxon, is correct)
  anova_matrix_correct = filter(anova_matrix, taxon == taxonomy[i], is_correct == TRUE)
  anova_matrix_correct = select(anova_matrix_correct, response_time, treatment)
  print(summary(aov(response_time ~ treatment, anova_matrix_correct)))
}
## [1] "CL"
                Df Sum Sq Mean Sq F value Pr(>F)
##
                    3289
                            822.3
                                    1.044 0.385
## treatment
               228 179505
## Residuals
                            787.3
## [1] "CO"
##
                Df Sum Sq Mean Sq F value Pr(>F)
## treatment
                4
                     2558
                            639.5
                                    3.975 0.00383 **
               244 39259
## Residuals
                            160.9
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## [1] "DC"
##
                Df Sum Sq Mean Sq F value Pr(>F)
                            525.4
                                   3.572 0.00748 **
## treatment
                    2102
## Residuals
               245 36041
                            147.1
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## [1] "RE"
##
                Df Sum Sq Mean Sq F value Pr(>F)
                4
                      260
                            65.03
                                    1.128 0.344
## treatment
               270 15563
                            57.64
## Residuals
## [1] "SU"
##
               Df Sum Sq Mean Sq F value Pr(>F)
## treatment
                4
                    1652
                            412.9
                                    1.024 0.398
               117 47159
## Residuals
                            403.1
## [1] "FA"
##
                Df Sum Sq Mean Sq F value Pr(>F)
## treatment
                     309
                           77.17
                                    0.812 0.518
## Residuals
               261 24806
                            95.04
## [1] "FL"
                Df Sum Sq Mean Sq F value Pr(>F)
##
## treatment
                    2418
                            604.4
                                    1.247 0.292
## Residuals
               225 109083
                            484.8
## [1] "FT"
##
                Df Sum Sq Mean Sq F value Pr(>F)
## treatment
                4
                     1838
                            459.5
                                    1.217 0.304
## Residuals
               264 99677
                            377.6
```