Homework 6

Contents

importing libraries used

```
library('tidyverse')
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.5     v dplyr   1.0.7
## v tidyr   1.1.4     v stringr 1.4.0
## v readr   2.0.2     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library('emmeans')
library('afex')
```

```
## Loading required package: lme4

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
```

```
## ************
## Welcome to afex. For support visit: http://afex.singmann.science/

## - Functions for ANOVAs: aov_car(), aov_ez(), and aov_4()
## - Methods for calculating p-values with mixed(): 'S', 'KR', 'LRT', and 'PB'
## - 'afex_aov' and 'mixed' objects can be passed to emmeans() for follow-up tests
## - NEWS: emmeans() for ANOVA models now uses model = 'multivariate' as default.
## - Get and set global package options with: afex_options()
## - Set orthogonal sum-to-zero contrasts globally: set_sum_contrasts()
## - For example analyses see: browseVignettes("afex")
## ************

##
## Attaching package: 'afex'

## The following object is masked from 'package:lme4':
##
##     lmer
```

```
library('cowplot')
```

Past research has shown that people consistently believe that others are more easily manipulated by external influences than they themselves are – a phenomenon called the third-person effect (Davison, 1983). Cornwell and Krantz (2014) have investigated whether support for public policies aimed at changing behavior using incentives and other decision "nudges" is affected by this bias. To this end, they have asked participants to rate their support for various policies in different presentation formats. In their Study 2, participants were randomly assigned to one of four conditions, a second-person condition ("you"), a third-person condition ("people"), and two further control conditions.

For each policy, participants were asked to indicate the degree (on scales from 1 to 7) to which they support such a policy (1 indicating "not at all" and 7 indicating "very strongly"), the degree to which they thought the policy was likely to achieve its intended goals (1 indicating "very unlikely" and 7 indicating "very likely"), and the degree to which they thought the policy would result in unintended consequences (with, again, 1 indicating "very unlikely" and 7 indicating "very likely"). Each participant provided responses for 8 of the 16 different scenarios.

The main hypothesis was that the third-person perspective will lead to higher support judgments than the second-person perspective. An additional research question was whether the level of the support of the third-person perspective or the second-person perspective differed from the more neutral (passive) and no-justification conditions.

import the dataset:

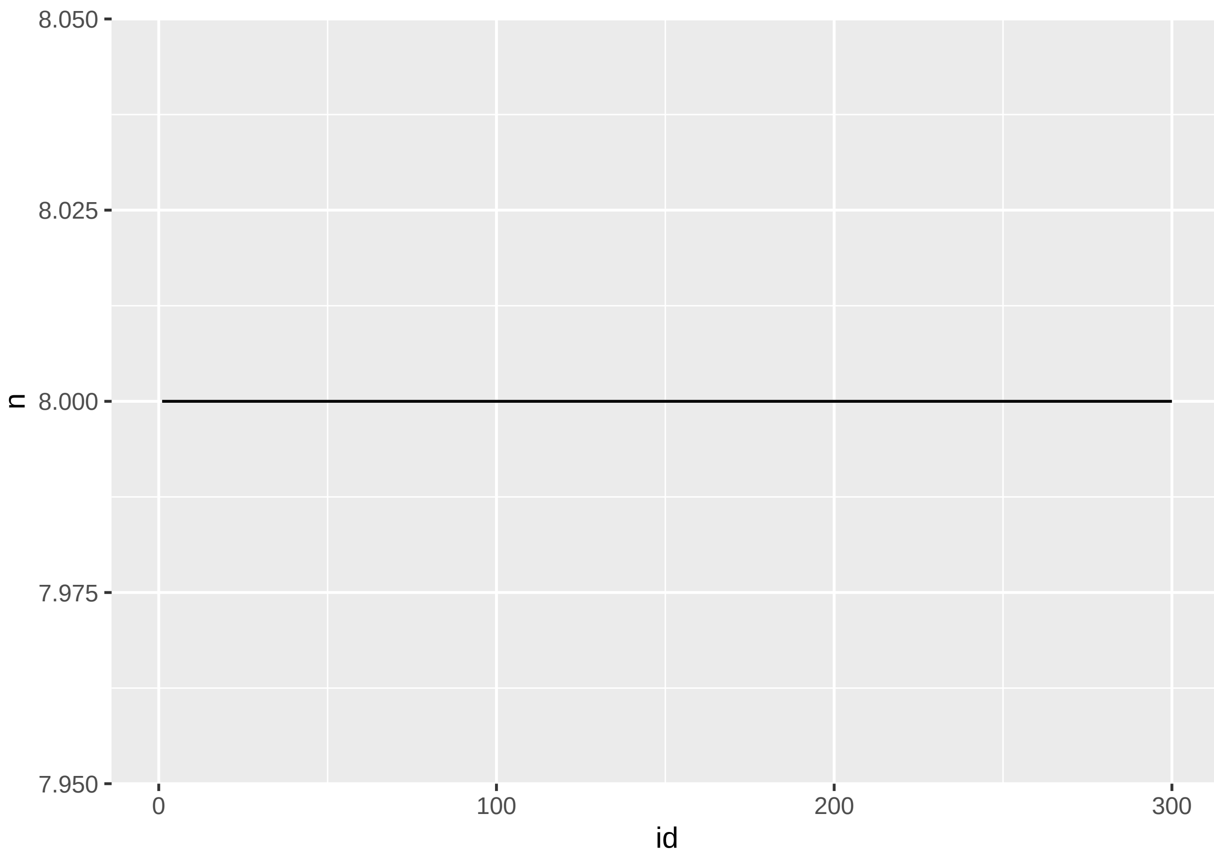
```
d1 <- read_csv("cornwell_krantz_2014_s2.csv") %>%
  mutate(
    condition =
      factor(
        condition,
        levels = 1:4,
        labels = c("third-person", "second-person", "passive", "no-justification")
      ))
head(d1)
```

```
## # A tibble: 6 x 23
##      id condition    scenario support achieve unintended agency1 agency2 agency3
##   <dbl> <fct>           <dbl>   <dbl>   <dbl>      <dbl>   <dbl>   <dbl>   <dbl>
## 1     1 no-justific~        2       7       5          1       2       3       7
## 2     1 no-justific~        5       7       7          3       2       3       7
## 3     1 no-justific~        7       6       6          1       2       3       7
## 4     1 no-justific~        8       7       7          1       2       3       7
## 5     1 no-justific~        9       4       4          7       2       3       7
## 6     1 no-justific~       10       3       3          6       2       3       7
## # ... with 14 more variables: agency4 <dbl>, agency5 <dbl>, agency6 <dbl>,
## #   personalpeople <dbl>, politics <dbl>, sex <dbl>, edu <dbl>, state <dbl>,
## #   income <dbl>, hispanic <dbl>, race <dbl>, suspicious <chr>, comments <chr>,
## #   notes <chr>
```

1 Task 1

```
d1 %>% group_by(id) %>% summarise(n=n()) %>% ggplot(aes(x=id,y=n)) + geom_line()
```

1.0.0.1 Count the number of observations (i.e., rows) for each of the participants. Do all participants have the same number of observations?



There are 8 observations per participant and all participants have the same number of observations

```r
d1 %>% group_by(condition) %>% summarise(n=n_distinct(id))
```

1.0.0.2 Count the number of participants per `condition`

```
## # A tibble: 4 x 2
##   condition           n
##   <fct>           <int>
## 1 third-person       74
## 2 second-person      77
## 3 passive            76
## 4 no-justification   73
```

```r
(t1 <- d1 %>% group_by(scenario,condition) %>% summarise(n=n()) %>%
   pivot_wider(names_from=condition,values_from=n))
```

1.0.0.3 Create a `tibble` for which the first column is `scenario` and columns two to five each contain the number of times each scenario appeared in one of the conditions (i.e., column two to five each contain the number of times a scenario appeared for one condition)

```
## # A tibble: 16 x 5
## # Groups:   scenario [16]
##    scenario `third-person` `second-person` passive `no-justification`
##       <dbl>          <int>           <int>   <int>              <int>
##  1        1             42              41      38                 36
##  2        2             34              38      37                 36
##  3        3             38              39      39                 36
##  4        4             37              38      39                 34
##  5        5             40              40      40                 37
##  6        6             35              37      39                 37
##  7        7             36              37      38                 38
##  8        8             36              39      35                 36
##  9        9             35              37      39                 37
## 10       10             37              37      36                 35
## 11       11             36              38      38                 37
## 12       12             37              39      39                 38
## 13       13             40              39      38                 37
## 14       14             35              39      37                 38
## 15       15             36              38      37                 37
## 16       16             38              40      39                 35
```

2 Task 2

Calculate three ANOVAs with IV `condition` and three different DVs, `support`, `achieve`, and `unintended`, using `afex`.

```r
a1 <- aov_car(support ~ condition + Error(id), d1)
```

```
## Contrasts set to contr.sum for the following variables: condition
```

```r
a2 <- aov_car(achieve ~ condition + Error(id), d1)
```

```
## Contrasts set to contr.sum for the following variables: condition
```

```r
a3 <-  aov_car(unintended ~ condition + Error(id), d1)
```

```
## Contrasts set to contr.sum for the following variables: condition
```

The ANOVA tests the following hypotheses:

$H_0 : The\ effects\ on\ the\ DV\ are\ equal\ across\ all\ conditions\ v.\ H_1 : For\ at\ least\ one\ condition,\ the\ effects\ on\ the\ DV\ differ$

```r
a1
```

```
## Anova Table (Type 3 tests)
##
## Response: support
##      Effect     df  MSE      F  ges p.value
## 1 condition 3, 296 1.28 2.16 + .021    .093
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

For `support` the conditions are only statistically significant at the 10% level. For significance levels of under 10%, we fail to reject the null hypothesis that support levels are the same across the different conditions

```r
a2
```

```
## Anova Table (Type 3 tests)
##
## Response: achieve
##      Effect     df  MSE      F  ges p.value
## 1 condition 3, 296 1.01 3.63 * .035    .013
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

For `achieve`, we reject the null hypothesis at the 5% significance level that achieve levels are the same across the different conditions.

```r
a3
```

```
## Anova Table (Type 3 tests)
##
## Response: unintended
##      Effect     df  MSE    F  ges p.value
## 1 condition 3, 296 0.91 0.15 .002    .926
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

We fail to reject the null hypothesis that unintended levels are the same across different conditions

3 Task 3

Produce a single composite score `acceptability` from the three variables `support`, `achieve`, and `unintended`. Create this such that higher values indicate a higher acceptability (i.e., support) for the respective policy (i.e., make sure to re-code variables as necessary).

Calculate an ANOVA with factor `condition` on the composite score `acceptability`. Calculate this ANOVA once using `afex` and once using the combination of `lm` and `car::Anova()`.

First, creating the composite variable `acceptability` given by the following equation:

$$acceptability = \frac{support + achieve + (8 - unintended)}{3}$$

```
d1 <- d1 %>% mutate(acceptability=(support + achieve + (8-unintended))/3)
```

Then, calculating ANOVA for `acceptability` using `afex`

```
a4 <- aov_car(acceptability ~ condition + Error(id), d1)
```

```
## Contrasts set to contr.sum for the following variables: condition
```

```
a4
```

```
## Anova Table (Type 3 tests)
##
## Response: acceptability
##      Effect     df  MSE      F  ges p.value
## 1 condition 3, 296 0.74 2.18 + .022    .091
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

For `acceptability` the conditions are only statistically significant at the 10% level. For significance levels of under 10%, we fail to reject the null hypothesis that acceptability levels are the same across the different conditions.

Comparing with `car::Anova()`

```
l1 <- lm(acceptability ~ condition, d1)
car::Anova(l1,type=3)
```

```
## Anova Table (Type III tests)
##
## Response: acceptability
##             Sum Sq   Df   F value  Pr(>F)
## (Intercept) 9525.4    1 3442.0397 < 2e-16 ***
## condition     38.8    3    4.6709 0.00294 **
## Residuals   6630.6 2396
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

This gives us different results because it is run on unaggregated data unlike `afex` which automatically aggregates data using the mean when there are more than one observations per cell.

Aggregating data per participant using mean and then running `car::Anova()`

```r
d2 <- d1 %>% group_by(id,condition) %>% summarise(support=mean(support),achieve=mean(achieve),unintended
                                                   acceptability=mean(acceptability))
head(d2)
```

```
## # A tibble: 6 x 6
## # Groups:   id [6]
##      id condition        support achieve unintended acceptability
##   <dbl> <fct>              <dbl>   <dbl>      <dbl>         <dbl>
## 1     1 no-justification    6       5.62       3             5.54
## 2     2 no-justification    4.88    3.75       3.88          4.25
## 3     3 passive             4.5     4.38       4.5           4.12
## 4     4 third-person        3.25    2.62       2             3.96
## 5     5 passive             1.88    4.12       5.25          2.92
## 6     6 third-person        4.5     4.5        4.38          4.21
```

```r
l2 <- lm(acceptability ~ condition, d2)
car::Anova(l2,type=3)
```

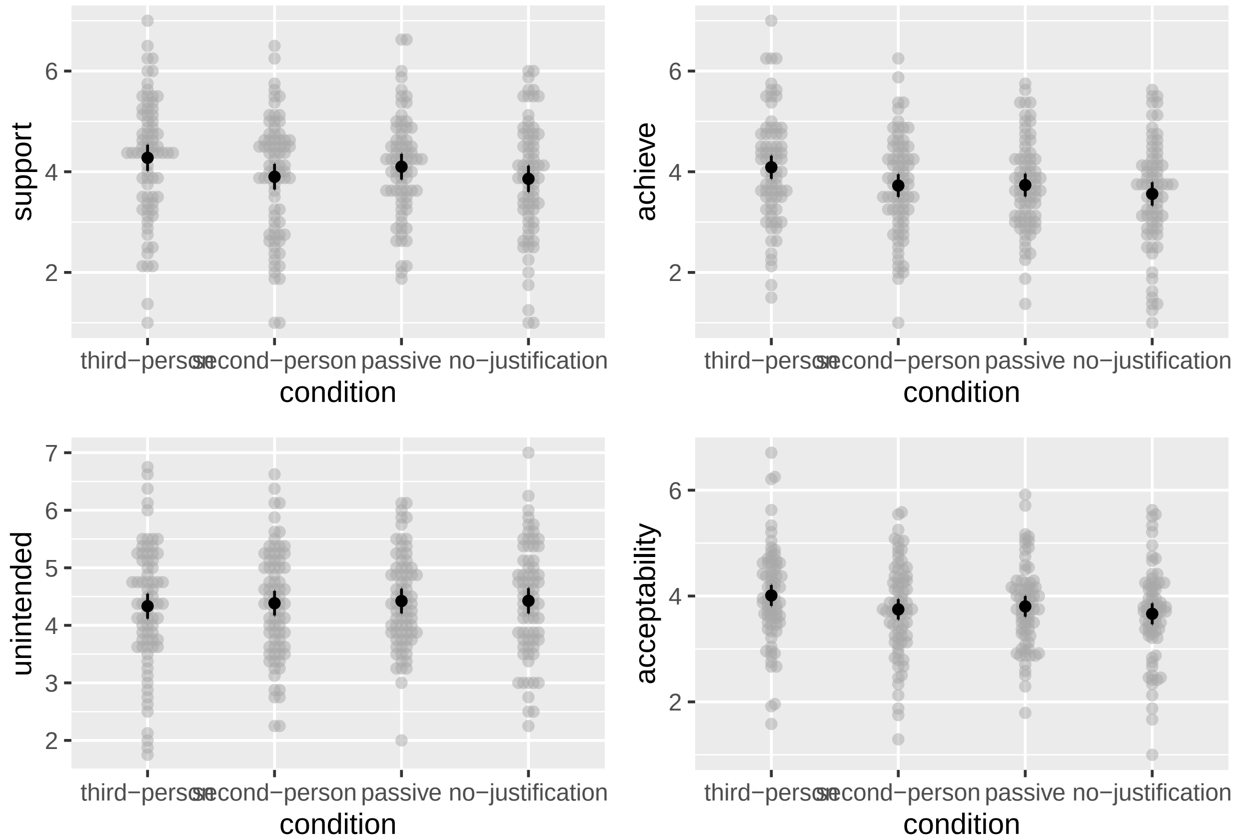
```
## Anova Table (Type III tests)
##
## Response: acceptability
##              Sum Sq  Df   F value  Pr(>F)
## (Intercept) 1190.68   1 1606.1948 < 2e-16 ***
## condition      4.85   3    2.1796 0.09051 .
## Residuals    219.43 296
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Now they produce identical outputs.

4 Task 4

Create a plot for each of the four ANOVAs calculated so far.

```r
p1 <- afex_plot(a1,'condition')
p2 <- afex_plot(a2,'condition')
p3 <- afex_plot(a3,'condition')
p4 <- afex_plot(a4,'condition')
plot_grid(p1,p2,p3,p4,nrow=2)
```



5 Task 5

Apply the following contrasts to the ANOVA(s) with a significant effect of condition as well as the ANOVA with acceptability as DV. The contrasts should compare the means of the following conditions (or combination of conditions): * Third person versus other conditions (i.e., mean of other conditions).

```
c1 <- list(III_v_other=c(1,-1/3,-1/3,-1/3))
```

- Third person versus second person.

```
c2 <- list(III_v_II=c(1,-1,0,0))
```

- Third person versus second and passive.

```
c3 <- list(III_v_IIandP=c(1,-1/2,-1/2,0))
```

- Second person versus other conditions.

```
c4 <- list(II_v_other=c(-1/3,1,-1/3,-1/3))
```

- Three contrasts, each testing the no-justification versus one of the other conditions.

```
c5 <- list(NJ_v_III=c(-1,0,0,1))
c6 <- list(NJ_v_II=c(0,-1,0,1))
c7 <- list(NJ_v_P=c(0,0,-1,1))
```

Only `achieve` was statistically significant.

`emmeans` for `achieve`:

```
(e1 <- emmeans(a2,'condition'))
```

```
##  condition        emmean    SE  df lower.CL upper.CL
##  third-person       4.09 0.117 296     3.86     4.32
##  second-person      3.73 0.115 296     3.50     3.95
##  passive            3.74 0.115 296     3.51     3.96
##  no-justification   3.56 0.118 296     3.33     3.79
##
## Confidence level used: 0.95
```

`emmeans` for `acceptability`

```
(e2 <- emmeans(a4,'condition'))
```

```
##  condition        emmean     SE  df lower.CL upper.CL
##  third-person       4.01 0.1001 296     3.81     4.21
##  second-person      3.75 0.0981 296     3.55     3.94
##  passive            3.80 0.0988 296     3.61     4.00
##  no-justification   3.66 0.1008 296     3.47     3.86
##
## Confidence level used: 0.95
```

Constructing a list of contrasts:

```
contrasts = list(c1,c2,c3,c4,c5,c6,c7)
```

Contrasts for `achieve`:

```
for (c in contrasts) {
  print(contrast(e1,c))
}
```

```
##  contrast    estimate    SE  df t.ratio p.value
##  III_v_other    0.416 0.135 296   3.089  0.0022
##
##  contrast estimate    SE  df t.ratio p.value
##  III_v_II    0.364 0.164 296   2.223  0.0269
##
##  contrast     estimate    SE  df t.ratio p.value
##  III_v_IIandP    0.359 0.142 296   2.523  0.0122
##
##  contrast   estimate    SE  df t.ratio p.value
##  II_v_other  -0.0692 0.133 296  -0.521  0.6028
```

```
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_III    -0.53 0.166 296  -3.193  0.0016
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_II    -0.166 0.164 296  -1.009  0.3138
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_P     -0.175 0.165 296  -1.064  0.2883
```

Contrasts for `acceptability`:

```
for (c in contrasts) {
  print(contrast(e2,c,adjust='holm'))
}
```

```
##  contrast    estimate    SE  df t.ratio p.value
##  III_v_other    0.273 0.115 296   2.364  0.0187
##
##  contrast estimate   SE  df t.ratio p.value
##  III_v_II    0.264 0.14 296   1.883  0.0606
##
##  contrast     estimate    SE  df t.ratio p.value
##  III_v_IIandP    0.235 0.122 296   1.931  0.0544
##
##  contrast   estimate    SE  df t.ratio p.value
##  II_v_other  -0.0793 0.114 296  -0.697  0.4862
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_III   -0.347 0.142 296  -2.442  0.0152
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_II   -0.0829 0.141 296  -0.589  0.5560
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_P      -0.14 0.141 296  -0.991  0.3223
```

5.0.0.1 Which of the contrasts are significant for the ANOVA(s) with a significant effect of condition?

Significant contrasts when considering `achieve` are the third-person v. all others; third-person v. second-person; third-person v. second-person and passive; and no-justification v. third-person. This implies that the third-person condition achieves better `achieve` scores while the no-justification achieves the worst `achieve` scores. The results of the other conditions relatively speaking are inconclusive.

When considering `acceptability`, only third-person v. other; and no-justification v. third-person are statistically significant at least the 5% level. This has the same implictaion as above but for `acceptability` scores.

```
for (c in contrasts) {
  print(contrast(e1,c,adjust='holm'))
}
```

5.0.0.2 Does the pattern of significant contrasts change if you do not control for multiple testing compared to when using the Bonferroni-Holm method?

```
##  contrast    estimate    SE  df t.ratio p.value
##  III_v_other    0.416 0.135 296   3.089  0.0022
##
##  contrast estimate    SE  df t.ratio p.value
##  III_v_II    0.364 0.164 296   2.223  0.0269
##
##  contrast     estimate    SE  df t.ratio p.value
##  III_v_IIandP    0.359 0.142 296   2.523  0.0122
##
##  contrast   estimate    SE  df t.ratio p.value
##  II_v_other  -0.0692 0.133 296  -0.521  0.6028
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_III    -0.53 0.166 296  -3.193  0.0016
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_II    -0.166 0.164 296  -1.009  0.3138
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_P     -0.175 0.165 296  -1.064  0.2883
```

```
for (c in contrasts) {
  print(contrast(e2,c,adjust='holm'))
}
```

```
##  contrast    estimate    SE  df t.ratio p.value
##  III_v_other    0.273 0.115 296   2.364  0.0187
##
##  contrast estimate   SE  df t.ratio p.value
##  III_v_II    0.264 0.14 296   1.883  0.0606
##
##  contrast     estimate    SE  df t.ratio p.value
##  III_v_IIandP    0.235 0.122 296   1.931  0.0544
##
##  contrast   estimate    SE  df t.ratio p.value
##  II_v_other  -0.0793 0.114 296  -0.697  0.4862
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_III   -0.347 0.142 296  -2.442  0.0152
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_II   -0.0829 0.141 296  -0.589  0.5560
##
##  contrast estimate    SE  df t.ratio p.value
##  NJ_v_P      -0.14 0.141 296  -0.991  0.3223
```

Thus, the results are the same regardless of control for multiple testing.

5.0.0.3 Which contrasts do you think are the most relevant to the research questions? Apply those contrasts using the Bonferroni-Holm method. Which substantive conclusions are

justified, given these results? According to the research question, the contrasts which are relevant are: third-person v. second-person; third-person and second-person v. no-justification and passive; third-person v. no-justification and passive; and second-person v. no-justification and passive.

```
c8 <- list(IIInII_v_NJnP=c(1/2,1/2,-1/2,-1/2))
c9 <- list(III_v_NJnP=c(1,0,-1/2,-1/2))
c10 <- list(II_v_NJnP=c(0,1,-1/2,-1/2))
contrasts2 <- list(c2,c8,c9,c10)
for (c in contrasts2) {
  print(contrast(e2,c,adjust='holm'))
}
```

```
##  contrast estimate   SE  df t.ratio p.value
##  III_v_II    0.264 0.14 296   1.883  0.0606
##
##  contrast      estimate     SE  df t.ratio p.value
##  IIInII_v_NJnP    0.145 0.0994 296   1.458  0.1460
##
##  contrast   estimate    SE  df t.ratio p.value
##  III_v_NJnP    0.277 0.122 296   2.262  0.0245
##
##  contrast  estimate    SE  df t.ratio p.value
##  II_v_NJnP    0.013 0.121 296   0.107  0.9146
```

Therefore, the conclusion that the third-person condition performs best in increasing `acceptability` as compared to the other conditions hold true given the statistical significance of the relevant contrasts.

6 Task 6

Calculate the means and standard errors for the `acceptability` scores per condition (after aggregating the different observations per participant). Compare these values with the means and standard errors that are returned by `emmeans` for the ANOVA on acceptability scores. How can you explain the (small) differences?

First, calling the `emmeans` calculated for `acceptability`

```
e2
```

```
##  condition        emmean     SE  df lower.CL upper.CL
##  third-person       4.01 0.1001 296     3.81     4.21
##  second-person      3.75 0.0981 296     3.55     3.94
##  passive            3.80 0.0988 296     3.61     4.00
##  no-justification   3.66 0.1008 296     3.47     3.86
##
## Confidence level used: 0.95
```

Calculating means and standard errors ‘manually’:

```
s1 <- d2 %>% group_by(condition) %>% summarise(avg=mean(acceptability),se1=sd(acceptability)/sqrt(n()))
s1
```

```
## # A tibble: 4 x 3
##   condition          avg    se1
##   <fct>             <dbl>  <dbl>
## 1 third-person      4.01 0.107
## 2 second-person     3.75 0.0988
## 3 passive           3.80 0.0882
## 4 no-justification  3.66 0.103
```

While the means are the same between the two, note the difference in standard errors. The ones calculated 'manually' are slightly larger. This is because `emmeans` uses the residual standard error in its calulcation collected from the `lm` regression while when calculating it 'manually' the standard deviation is the standard deviation of `acceptability` for each condition. Thus, this results in small differences between the two. To get the 'correct' standard errors, this can be done by simply using the standard deviation from the original regression instead:

```
summary(lm(acceptability~condition,d2))
```

```
##
## Call:
## lm(formula = acceptability ~ condition, data = d2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.66438 -0.45977  0.00271  0.50239  2.69707
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  4.0113     0.1001  40.077   <2e-16 ***
## conditionsecond-person      -0.2640     0.1402  -1.883   0.0606 .
## conditionpassive            -0.2070     0.1406  -1.472   0.1421
## conditionno-justification  -0.3469     0.1420  -2.442   0.0152 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.861 on 296 degrees of freedom
## Multiple R-squared:  0.02161,    Adjusted R-squared:  0.0117
## F-statistic:  2.18 on 3 and 296 DF,  p-value: 0.09051
```

The standard error is 0.861:

```
(s2 <- d2 %>% group_by(condition) %>% summarise(mean=mean(acceptability),se2=(0.861/sqrt(n()))))
```

```
## # A tibble: 4 x 3
##   condition          mean    se2
##   <fct>             <dbl>  <dbl>
## 1 third-person      4.01 0.100
## 2 second-person     3.75 0.0981
## 3 passive           3.80 0.0988
## 4 no-justification  3.66 0.101
```

```r
e2
```

```
##  condition        emmean     SE  df lower.CL upper.CL
##  third-person       4.01 0.1001 296     3.81     4.21
##  second-person      3.75 0.0981 296     3.55     3.94
##  passive            3.80 0.0988 296     3.61     4.00
##  no-justification   3.66 0.1008 296     3.47     3.86
##
## Confidence level used: 0.95
```

Now, we get identical results.