Data Science Assignment 5

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```r
library(tidyverse)
library(lsr)
library(nortest)

data = read.table('./data/decision.dat', header = T)
data$isHighCoh = data$cohFac > .5
data$coherence = ifelse(data$isHighCoh == 0, "Low Coherence", "High Coherence")
dataNoErr = data %>% filter(ER == 0)
subj1NoErr = dataNoErr %>% filter(subjNo == 1, isDots == 1)
```

1 T-test

```r
subj1Low <- subj1NoErr %>% filter(isHighCoh == FALSE)
subj1High <- subj1NoErr %>% filter(isHighCoh == TRUE)
t.test(subj1Low$RT, subj1High$RT, paired = FALSE)
```

```
##
##  Welch Two Sample t-test
##
## data:  subj1Low$RT and subj1High$RT
## t = 11.63, df = 645.85, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.2741558 0.3855458
## sample estimates:
## mean of x mean of y
## 1.2268374 0.8969866
```

(a) In our case, as we only perform a t-test with one subject, it should be an independent samples t-test (i.e. we do not need to pair values as we only have one subject).

(b) A two-sample t-test was conducted to compare reaction times (RTs, in seconds) between low-coherence and high-coherence trials for subject 1. The average RT was significantly higher for low-coherence trials (M = 1.227 s, SD = 0.546) than for high-coherence trials (M = 0.897 s, SD = 0.296). This difference was statistically significant, $t(645.85) = 11.63$, $p < 0.001$, 95% CI [0.27, 0.39].

```r
rt_summary <- dataNoErr %>%
  group_by(subjNo, isHighCoh) %>%
  summarise(mean_RT = mean(RT))
```

```
## `summarise()` has grouped output by 'subjNo'. You can override using the
## `.groups` argument.
```

```r
LowCoh <- rt_summary$mean_RT[rt_summary$isHighCoh == FALSE]
HighCoh <- rt_summary$mean_RT[rt_summary$isHighCoh == TRUE]

t.test(LowCoh, HighCoh, paired = TRUE)
```

```
##
##  Paired t-test
##
## data:  LowCoh and HighCoh
## t = 4.9928, df = 22, p-value = 5.361e-05
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  0.0550208 0.1332042
## sample estimates:
## mean difference
##       0.0941125
```

(c) In this situation, we need a paired-samples t-test, as the experiment was run within subjects. The paired t-test compares the mean difference in reaction times between the two conditions, while also taking into account that participants took part in both conditions.

(d) A paired-samples t-test was conducted to compare reaction times between low-coherence and high-coherence trials. There was a significant difference in reaction times between the two conditions, $t(22) = 4.99$, $p < .001$, with response times being lower in the high-coherence condition (mean difference = 0.094, 95% CI [0.055, 0.133]).

2 Non-parametric alternatives

```r
wilcox.test(LowCoh, HighCoh, paired = TRUE)
```

```
##
##  Wilcoxon signed rank exact test
##
## data:  LowCoh and HighCoh
## V = 272, p-value = 1.669e-06
## alternative hypothesis: true location shift is not equal to 0
```

(a) In our case, the Wilcoxon signed-rank test would be the most suited choice, as it does not assume normality of the differences and it compares two related samples (i.e. paired data).

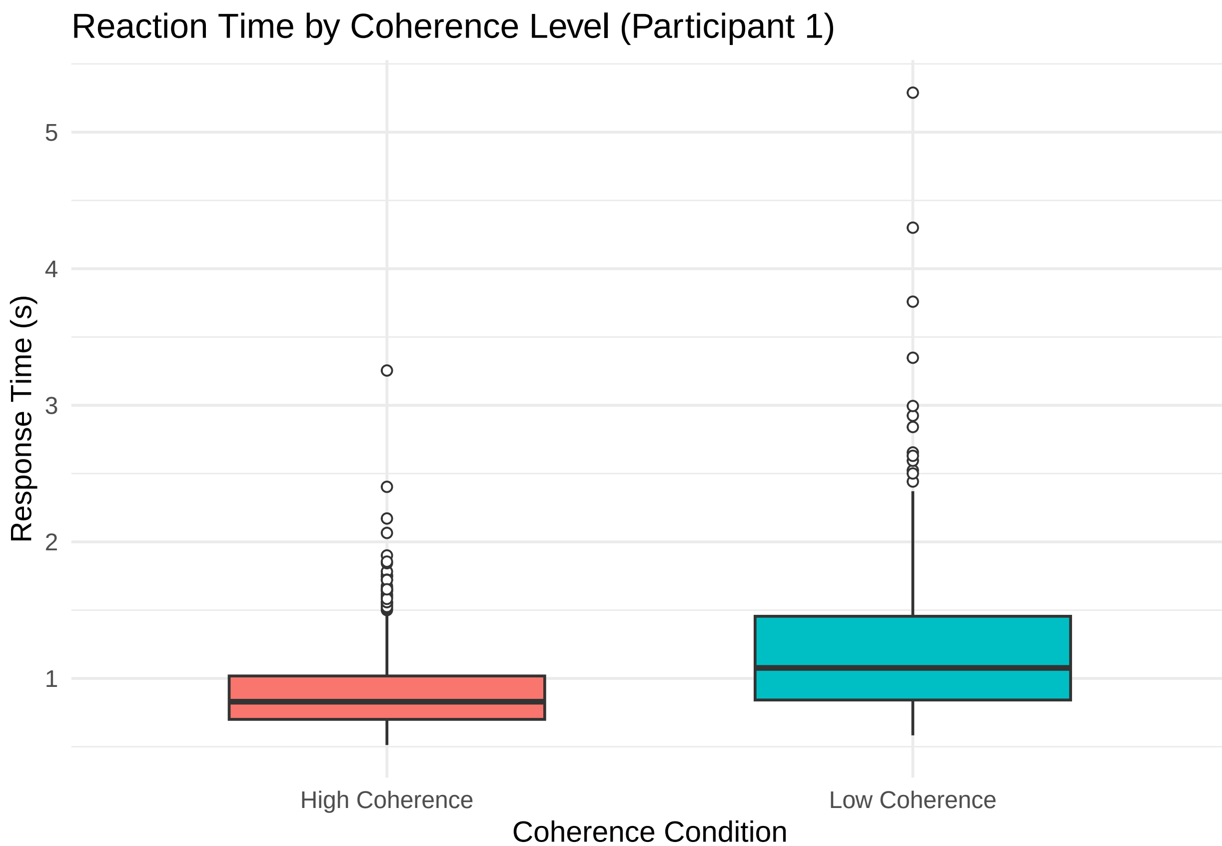
(b) A Wilcoxon signed-rank test was conducted to compare reaction times between low- and high-coherence conditions across participants. The test revealed a significant difference in reaction times, $V = 272$, $p < .001$, indicating that the median reaction time in the high-coherence condition was significantly lower than in the low-coherence condition.

3 One-way ANOVA

```r
resOneWay = aov(RT ~ isHighCoh, data = subj1NoErr)
summary(resOneWay)
```

```
##               Df Sum Sq Mean Sq F value Pr(>F)
## isHighCoh      1  28.23  28.228   159.1 <2e-16 ***
## Residuals   1059 187.91   0.177
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
ggplot(subj1NoErr, aes(x = coherence, y = RT, fill = coherence)) +
  geom_boxplot(width = 0.6, outlier.shape = 21, outlier.fill = "white") +
  labs(
    title = "Reaction Time by Coherence Level (Participant 1)",
    x = "Coherence Condition",
    y = "Response Time (s)"
  ) +
  theme_minimal() +
  theme(legend.position = "none")
```




```r
eta = etaSquared(resOneWay, type = 1)
summary(eta)
```

```
##      eta.sq        eta.sq.part
##  Min.   :0.1306   Min.   :0.1306
##  1st Qu.:0.1306   1st Qu.:0.1306
##  Median :0.1306   Median :0.1306
##  Mean   :0.1306   Mean   :0.1306
##  3rd Qu.:0.1306   3rd Qu.:0.1306
##  Max.   :0.1306   Max.   :0.1306
```

(a) A one-way ANOVA revealed a significant effect of coherence on response time for participant 1, F(1, 1059) = 159.1, $p < .001$. Participants responded significantly faster during high-coherence trials than during low-coherence trials.

(b) As we can notice, both the ANOVA and the two-samples t-test have the same result: participants responded significantly faster during high-coherence trials than during low-coherence trials.

(c) No, we don't need to correct for multiple comparisons in this case. Although we ran both a t-test and a one-way ANOVA, they were both testing the same hypothesis: whether response times differ between low and high coherence trials for participant 1. Multiple comparison correction is only needed when testing multiple hypotheses or doing several comparisons across different groups.

(d) We obtained $\eta^2 = 0.1161$. This means that approximately 11.6% of the variance in response time can be explained by the coherence level (high vs. low) for participant 1. According to the benchmarks from Lakens (2013), this represents a medium-to-large effect size.

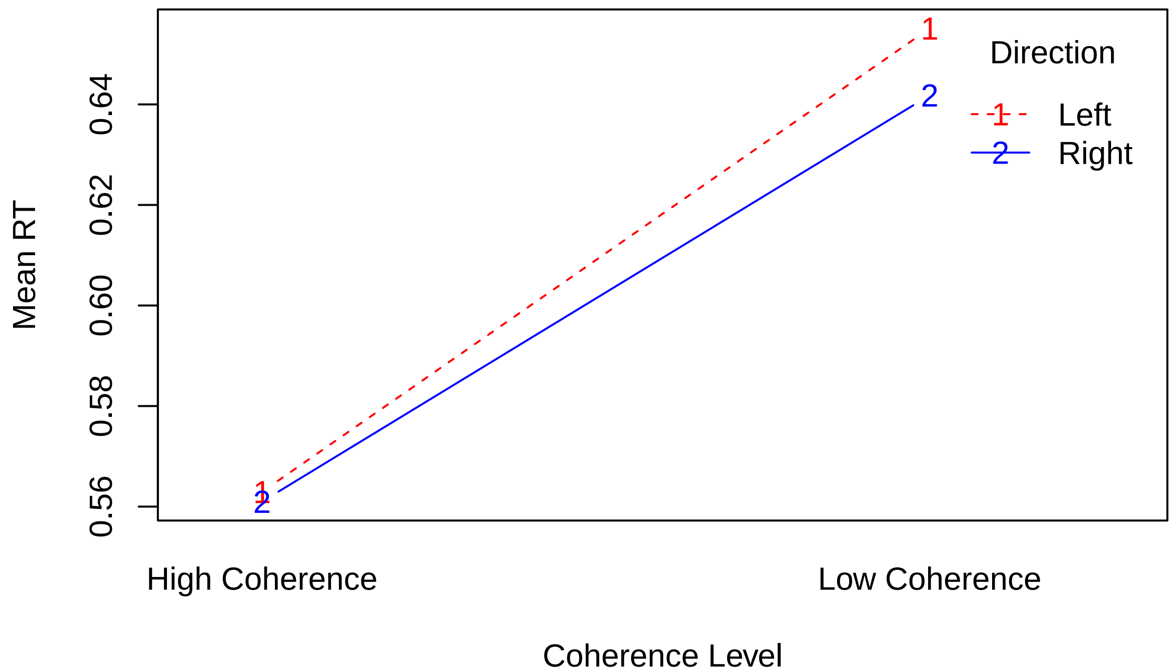
4 Two-way ANOVA

```r
resTwoWay = aov(RT ~ isHighCoh * isLeft, data = dataNoErr)
summary(resTwoWay)
```

```
##                     Df Sum Sq Mean Sq F value Pr(>F)
## isHighCoh            1     95   94.91 438.683 <2e-16 ***
## isLeft               1      1    0.64   2.971 0.0848 .
## isHighCoh:isLeft     1      0    0.41   1.897 0.1685
## Residuals        51230  11083    0.22
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
left =

interaction.plot(
  x.factor = dataNoErr$coherence,
  trace.factor = ifelse(dataNoErr$isLeft, "Left", "Right"),
  response = dataNoErr$RT,
  fun = mean,
  type = "b",
  col = c("red", "blue"),
  ylab = "Mean RT",
  xlab = "Coherence Level",
  legend = TRUE,
  trace.label = "Direction"
)
```



(a) A two-way ANOVA revealed a significant main effect of coherence, F(1, 51230) = 438.7, p < .001, indicating that participants responded faster on high-coherence trials than low-coherence trials. There was no significant main effect of direction, F(1, 51230) = 2.97, p = .0848, and no significant interaction between coherence and direction, F(1, 51230) = 1.90, p = .1685.

5 Repeated-measures ANOVA

```
resRep <- aov(
  RT ~ isHighCoh * isLeft + Error(subjNo / (isHighCoh * isLeft)),
  data = dataNoErr)

summary(data)
```

```
##      subjNo            ER                RT                 isLeft
##  Min.   : 1.00   Min.   :0.0000   Min.   :9.436e-04   Min.   :0.0000
##  1st Qu.: 7.00   1st Qu.:0.0000   1st Qu.:3.441e-01   1st Qu.:0.0000
##  Median :13.00   Median :0.0000   Median :4.769e-01   Median :0.0000
##  Mean   :13.88   Mean   :0.1105   Mean   :6.380e-01   Mean   :0.4959
##  3rd Qu.:22.00   3rd Qu.:0.0000   3rd Qu.:7.467e-01   3rd Qu.:1.0000
##  Max.   :27.00   Max.   :1.0000   Max.   :1.238e+01   Max.   :1.0000
##      cohVec           cohFac           blocknum          isDots
##  Min.   : 2.000   Min.   :0.0000   Min.   : 1.00   Min.   :0.0000
```

```
##  1st Qu.: 4.000   1st Qu.:0.0000   1st Qu.:16.00   1st Qu.:0.0000
##  Median : 7.000   Median :1.0000   Median :32.00   Median :1.0000
##  Mean   : 7.736   Mean   :0.5211   Mean   :32.25   Mean   :0.5024
##  3rd Qu.:12.000   3rd Qu.:1.0000   3rd Qu.:48.00   3rd Qu.:1.0000
##  Max.   :15.000   Max.   :1.0000   Max.   :64.00   Max.   :1.0000
##  isHighCoh         coherence
##  Mode :logical   Length:57597
##  FALSE:27581     Class :character
##  TRUE :30016     Mode  :character
##
##
##
```

```
group1 <- dataNoErr %>% filter(isHighCoh == 0, isLeft == 1)
group2 <- dataNoErr %>% filter(isHighCoh == 0, isLeft == 0)
group3 <- dataNoErr %>% filter(isHighCoh == 1, isLeft == 1)
group4 <- dataNoErr %>% filter(isHighCoh == 1, isLeft == 0)

lillie.test(group1$RT)
```

```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  group1$RT
## D = 0.24307, p-value < 2.2e-16
```

```
lillie.test(group2$RT)
```

```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  group2$RT
## D = 0.24105, p-value < 2.2e-16
```

```
lillie.test(group3$RT)
```

```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  group3$RT
## D = 0.19262, p-value < 2.2e-16
```

```
lillie.test(group4$RT)
```

```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  group4$RT
## D = 0.18312, p-value < 2.2e-16
```

(a) A repeated-measures ANOVA is more appropriate in this case because the same participants are tested in all conditions, so each participant contributes response times for both coherence levels (high and low) and both directions (left and right). This means the data are not independent, which is a key assumption of a regular two-way ANOVA. A repeated-measures ANOVA takes into account the within-subject structure of the data by modeling the variation due to individual differences.

(b) We conducted a repeated-measures ANOVA to examine the effects of coherence level (high vs low) and stimulus direction (left vs right) on response time, accounting for the fact that each participant experienced all conditions. There was a significant main effect of coherence, F(1, 51226) = 106.12, p < .001, indicating that participants responded faster on high-coherence trials compared to low-coherence trials. There was no significant main effect of direction, F(1, 51226) = 0.36, p = .551, and no significant interaction between coherence and direction, F(1, 51226) = 0.04, p = .852. This suggests that the effect of coherence on response time was consistent regardless of the stimulus direction. Compared to the regular two-way ANOVA in Question 4, the repeated-measures ANOVA produced a similar pattern of results, but is more appropriate for this within-subjects design and provides more reliable estimates by accounting for individual differences.

(c) One of the key assumptions of ANOVA is that the dependent variable (in this case, response time) is normally distributed within each condition. To test this, we ran the Lilliefors test for normality on the RT distributions in all four combinations of coherence level (high vs low) and stimulus direction (left vs right). In all four conditions, the test returned very low p-values ($< 2.2e - 16$), indicating a significant deviation from normality. Therefore, the assumption of normality is violated in this dataset. This suggests that a non-parametric alternative is more appropriate.

6 What test for what data?

(a) For a t-test, data that compares sleep duration (= dependent variable) between two groups would be suited. One group drank coffee before bed, the other did not (independent variable = coffee condition, 2 levels). A t-test is appropriate because it compares the means of two independent groups on a continuous variable.

(b) For a one-way ANOVA, data that compares weight loss (= dependent variable) between three groups would be suited. Participants follow either an omnivore, vegan, or low-carb diet (independent variable = diet type, 3 levels). A one-way ANOVA is appropriate because it compares the means of more than two independent groups on a continuous variable.

(c) For a two-way ANOVA, data that compares study performance (= dependent variable) based on two independent variables would be suited: music genre (classical vs. rock) and study environment (quiet vs. noisy), each with 2 levels. A two-way ANOVA is appropriate because it examines the main effects and interaction of two independent variables on a continuous outcome.

(d) For a repeated measures ANOVA, data that measures heart rate (= dependent variable) at multiple time points within the same participants would be suited. Heart rate is recorded before training, immediately after, and one hour later (independent variable = time, 3 within-subject levels). A repeated measures ANOVA is appropriate because it analyzes changes in a continuous variable across multiple conditions within the same subjects.