Methods 1 Portfolio

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Portfolio Contents:

Portfolio exam - Part 1 | Methods 1 F24, CogSci @AU

Søren Emil Skaarup, GROUP 3

01/10/2024

Assignment 01

Søren Emil Skaarup, 12/12/24

Group names

My group members' names are: [Asger, Sofie, Nele and Søren Emil]

Introduction

First of all, let's start by looking at the setup chunk. If you need to load packages or set your working directory, do so here:

```
knitr::opts_chunk$set(echo = TRUE, include = TRUE, message = FALSE, warning = FALSE)

library(tidyverse)
```

Now you have to import the personality data from the 'cogsci_personality_2024.csv' file; i.e., the one we have worked with in both class 2 and class 3. Note the filename is in lowercase and it is located in the /renv_cogsci_e23 folder on UCloud.

Once you have imported it, use the `head()` function to print the first 10 lines of the data set.

```
#loading data seperated by ; with delim function

data <- read_delim("/work/renv_cogsci_e24/CogSci_Personality_Test_2024.csv", delim =";")


#names


colnames(data) <- c("ID","shoesize","gender","native_Danish","handedness","choose_rand_num","touch_floor","hands_
touch_behind_back","2D4D","balloon_inflate","balloon_balance","breathhold","bad_choices","tongue_twist","romberg_
open","romberg_closed","ling_animal","ling_direct","ling_demonstr","ling_place","ling_abstract","ling_pronoun","l
ing_math","ling_activity","ling_adjective","ling_kiki","ocular_dom","vis_teddy","vis_pattern1","vis_duck","vis_sq
_face","vis_landscape","vis_animal","vis_emo","vis_house","vis_pattern2","hours_music_per_week","sound_level_pref
","aud_sound1","aud_sound2","aud_sound3","aud_instr1","aud_instr2","aud_vowels","taste_cola","taste_jam", "year")
```

Loaded the data.

Question 1

Question 1.1

Who can hold their breath the longest on average — those with right or left ocular dominance? Notice that the column is called `ocular_dom`, and that right ocular dominance is indicated in the column with 'Right', while left ocular dominance is indicated in the column with 'Left'. Therefore, you want to only filter out the data in this column which corresponds to either "Right" or "Left".

Answer to 1.1

To adress the problem, we will proceed methodically by the scientific method. Therefore we are adhering to statistical methods, to test our bold hypothesis against the status quo ie. the null hypothesis.

In this case our null hypotese, representing status quo, could be something like:

$$H_0 : \mu_r = \mu_l$$

And or alternative hypothesis, representing our bold conjecture, that ie. "ocular dominance correlates with breathold", could be represented like:

$$H_1 : \mu_r \neq \mu_l$$

We could test this hypothesis by comparing the sample mean, and trying to answer the question of whether or not they are derived from the same population:

$$\bar{X}_r = \bar{X}_l$$

So we are in the scenario, where we are trying to compare two samples, and asking whether or not, they derive from the same population.

```
#Assume following scheme
#Option 1 = left
#Option 2 = right

#Here one could run a for loop through the column to change the names, but we will not.


#Now I want to subset my datasets in distinction between ocular dominance.

#Using Tidyverse

data_lefteye_1 <- data[data$ocular_dom == "Option 1", ]

#Using base R

data_lefteye_2 <- data %>% filter(ocular_dom == "Option 1")

#Now for the right eye

data_righteye_2 <- data %>% filter(ocular_dom == "Option 2")



means <- c(mean(data_lefteye_1$breathhold), mean(data_righteye_2$breathhold))
means
```

```
## [1] 48.73077 54.57143
```

So now we have the numeric values of our estimators:

$$\bar{X}_l \approx 48$$

and

$$\bar{X}_r \approx 54$$

These are the ones, that could be subjects to our parametric t.test if we test for normality(shapiro-wilk) and similar variance(f-test ie. anova or var.test).

Plot the data using `ggplot2` to find out the answer to your question. The plots should include error bars depicting the standard error of the mean: you can add these using the `geom_errorbar()` function and specifying `stat = "summary", fun.data = "mean_se"`.

Now I would like to visualize the means and the error bars around it:

```
# Sample data
sample_data <- data.frame(
  sample = c("left", "right"),
  mean_value = means
)

# Calculating sd
sds <- c(sd(data_lefteye_1$breathhold), sd(data_righteye_2$breathhold))

# Calculating SE
SEs <- c(sds[1] / sqrt(length(data_lefteye_1$breathhold)), sds[2] / sqrt(length(data_righteye_2$breathhold)))
c(sds, SEs)
```

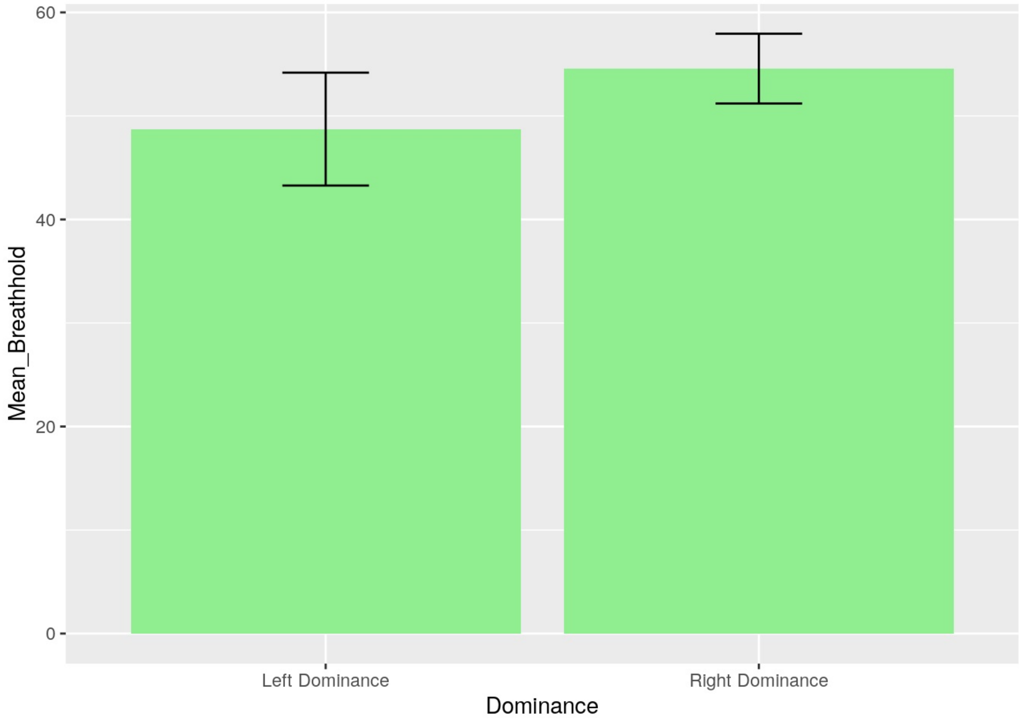
```
## [1] 27.804399 21.832112  5.452891  3.368768
```

```
# Data frame manipulation
sample_data <- sample_data %>%
  mutate(SE = c(SEs[1], SEs[2]),
         ymin = c(means[1] - SEs[1], means[2] - SEs[2]), # Fixing ymin for both samples
         ymax = c(means[1] + SEs[1], means[2] + SEs[2])) # Fixing ymax for both samples

# View sample data to confirm
sample_data
```

```
##   sample mean_value       SE     ymin     ymax
## 1   left   48.73077 5.452891 43.27788 54.18366
## 2  right   54.57143 3.368768 51.20266 57.94020
```

Now making a bar plot to visualize

```
data_ocular_mean <- c(mean(data_lefteye_2$breathhold), mean(data_righteye_2$breathhold))

df_od_plot<-data_frame(Dominance=c("Left Dominance","Right Dominance"), Mean_Breathhold = data_ocular_mean) %>%
    mutate(SE=c(SEs[1],SEs[2]),
           ymin=Mean_Breathhold-SE,
           ymax=Mean_Breathhold+SE)

ggplot(df_od_plot,
    aes(x = Dominance, y = Mean_Breathhold, fill = Dominance)) +
    geom_col() +
    geom_errorbar(aes(ymin = ymin, ymax = ymax), width = 0.2, position = position_dodge(0.9)) +
    scale_fill_manual(values = c("Left Dominance" = "lightgreen", "Right Dominance" = "lightgreen")) +
    theme(legend.position = "none")
```



The data has been visualized, and we are not seing any intuitive difference, in that the error bars are overlaping. This indicates that we are in lack of statistical evidence to reject the null.

Question 1.2

Summarizing the data

```
# Summarize data from left eye and add an identifying column
sum1 <- data_lefteye_1 %>%
  summarize(Mean = mean(breathhold),
            SD = sd(breathhold)) %>%
  mutate(Eye = "Left Eye")

# Summarize data from right eye and add an identifying column
sum2 <- data_righteye_2 %>%
  summarize(Mean = mean(breathhold),
            SD = sd(breathhold)) %>%
  mutate(Eye = "Right Eye")

#Here I am utilizing the bind_rows function to combine my to data frames by their row.
combined_summary <- bind_rows(sum1, sum2)

# View the combined summary
print(combined_summary)
```

```
## # A tibble: 2 × 3
##    Mean    SD Eye
##   <dbl> <dbl> <chr>
## 1  48.7  27.8 Left Eye
## 2  54.6  21.8 Right Eye
```

Explain your results in plain terms here (max 3 sentences):

In the current question 1.2: I am utlizing functions from our current library of packages, tidyverse, to manipulate our data. My goal was to create a dataframe, where the two main parameters of the normal distribution were clearly visible.

Overall, we can, by visual assesment, infer, that there is no significant statistical evidence speaking towards a correlation between eye and breathold. There seems to be no affect of eye dominance on breathold. This resonates with our a priori intuition from the biological sciences.

Question 2

Does gender have an effect on the preference silence or noise?

#####Seperating data by gender

```
#Defining subsets

women <- data %>% filter(gender=="female")
men <- data %>% filter(gender=="male")


#Amounts of observations

obs_women<-as.numeric(nrow(women))
obs_men<-as.numeric(nrow(men))
obs_total<-as.numeric(nrow(data))

#Checking vector length

obs_women+obs_men==obs_total
```

```
## [1] TRUE
```

I conclude that I have seperated correctly by the nrows function, by my verification.

#####Creatinng a summary

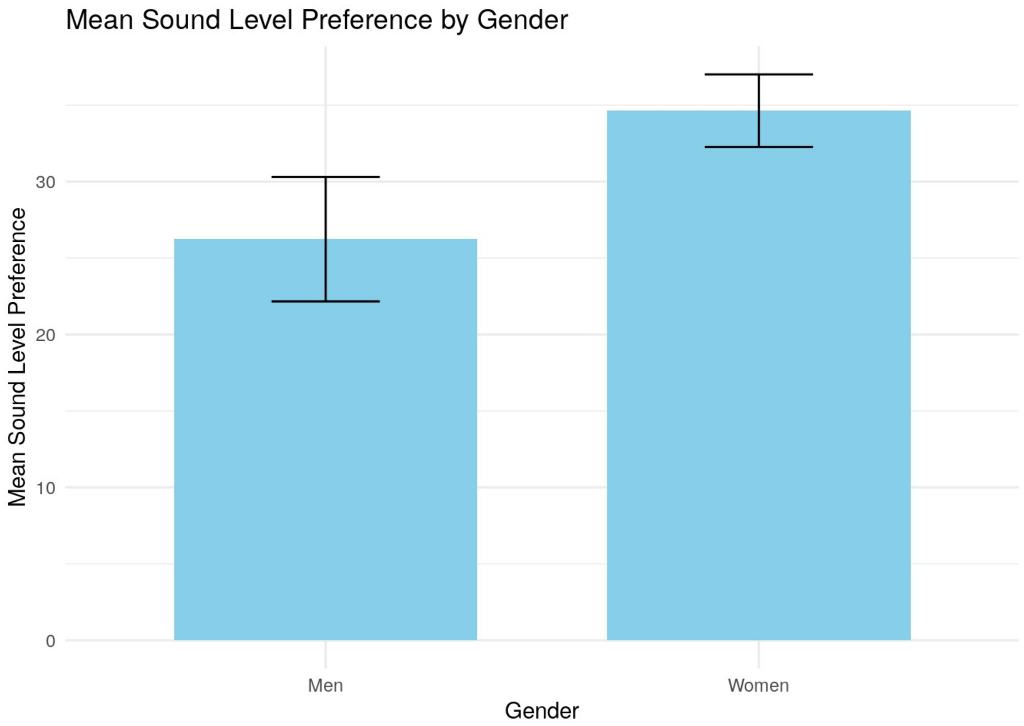
Now making the summary

```
# Summarize statistics for women
summary_women <- women %>%
  summarize(
    Group = "Women",                          # Add a column to identify the group
    Mean = mean(sound_level_pref),            # Calculate the mean
    SD = sd(sound_level_pref),                # Calculate the standard deviation
    SE = SD / sqrt(obs_women)                 # Calculate the standard error
  )

# Summarize statistics for men
summary_men <- men %>%
  summarize(
    Group = "Men",                            # Add a column to identify the group
    Mean = mean(sound_level_pref),            # Calculate the mean
    SD = sd(sound_level_pref),                # Calculate the standard deviation
    SE = SD / sqrt(obs_men)                   # Calculate the standard error
  )

# Combine the two summaries into one data frame
combined_summary <- bind_rows(summary_women, summary_men)

# Print the combined summary
print(combined_summary)
```

```
## # A tibble: 2 × 4
##   Group  Mean    SD    SE
##   <chr> <dbl> <dbl> <dbl>
## 1 Women  34.6  17.3  2.37
## 2 Men    26.2  18.6  4.07
```

#####Creating barplot

```
# Here I am adding columns for ymin and ymax to create error bars
combined_summary <- combined_summary %>%
  mutate(
    ymin = Mean - SE,  # Lower bound of error bar
    ymax = Mean + SE   # Upper bound of error bar
  )



# Create the bar plot with error bars
ggplot(combined_summary, aes(x = Group, y = Mean)) +
  geom_bar(stat = "identity", fill = "skyblue", width = 0.7) + # Bar plot with specific width
  geom_errorbar(aes(ymin = ymin, ymax = ymax), width = 0.25, position = position_dodge(0.91)) + # Error bars
  labs(title = "Mean Sound Level Preference by Gender",
       x = "Gender",
       y = "Mean Sound Level Preference") +  # Labels
  theme_minimal()  # Minimalistic theme
```



It seems there is a tendency towards a significant difference between men and women in terms of what sound level they prefer.

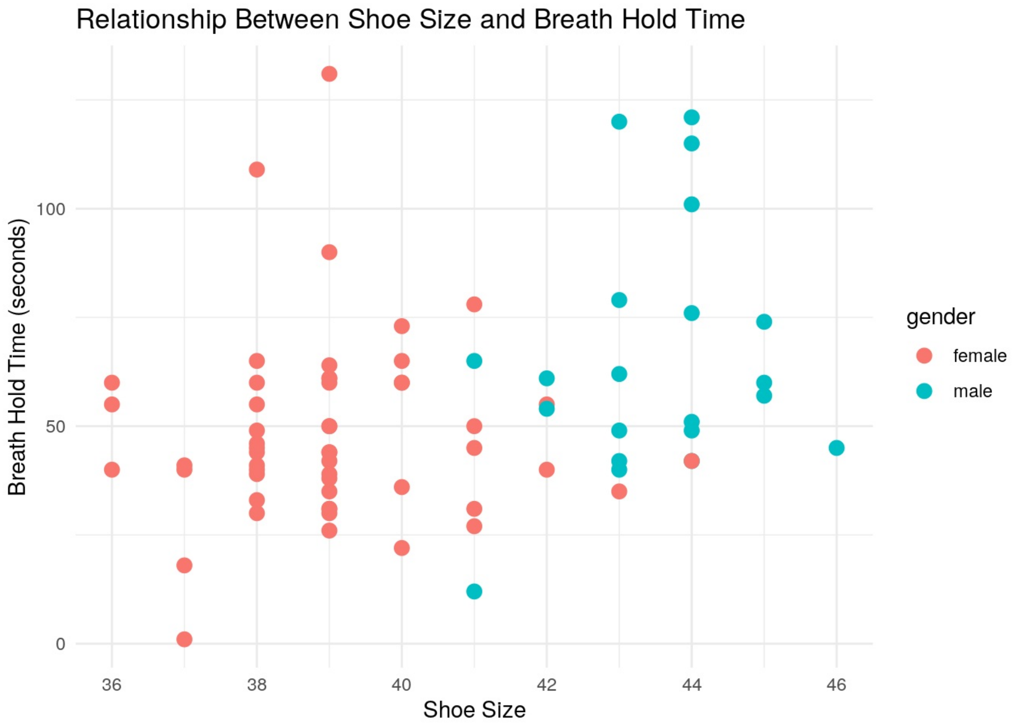
Explain your results in plain terms here (max 3 sentences):

I have sought to replicate the doings of question 1. I have tried to optimize my structure, so that my syntax is more clear, and my code is more understandable.

Question 3

Shoe size could tell us something about general body size, which could also be related to one's ability to hold your breath. In other words we predict that there is a positive relation between shoe size and how long time CogSci students can hold their breath.

```
# Using the ggplot function
library(ggplot2)

# Create scatter plot using ggplot
#I am using the aes function for aesthetics, and specifying the color, to the factor variable of gender:

ggplot(data, aes(x = shoesize, y = breathhold, color = gender)) +
  geom_point(size = 3) +  # Use larger points for better visibility
  labs(
    title = "Relationship Between Shoe Size and Breath Hold Time",
    x = "Shoe Size",
    y = "Breath Hold Time (seconds)"
  ) +
  theme_minimal()
```



Explain your results in plain terms here (max 3 sentences):

Our numerical observations might hint towards a slight positive correlation between shoe size and breathhold, even though we have heavy outliers, for example

```
max(data$breathhold)
```

```
## [1] 131
```

which by our plot is a female participant, with quite the low weight.

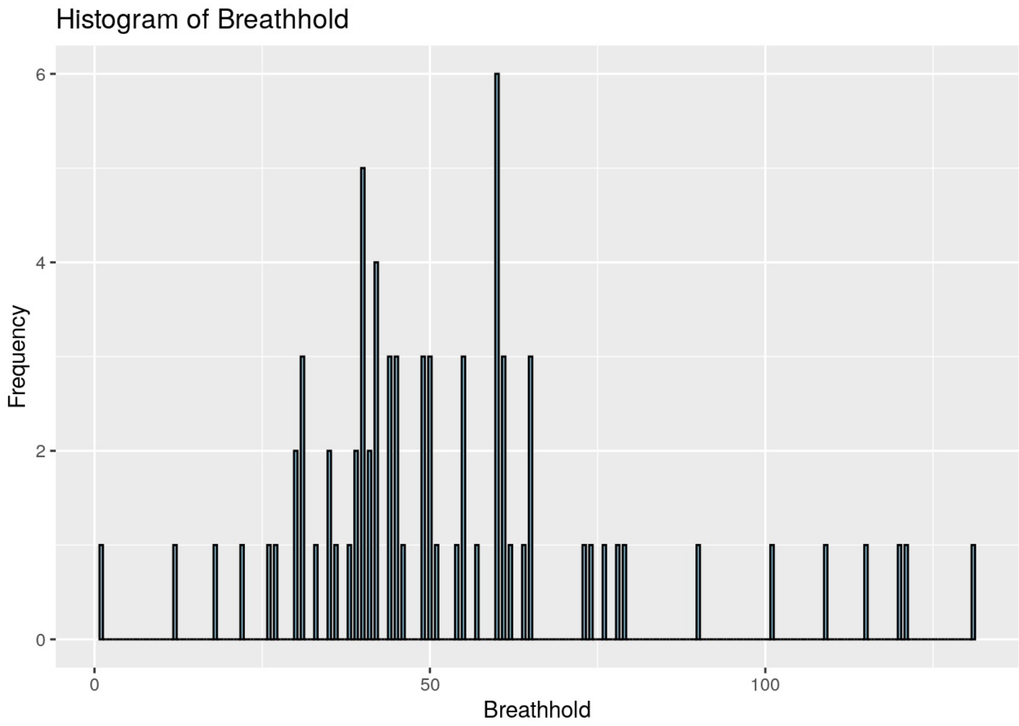
I don't find data suggest a very strong correlation.

Question 4

Is the `breathhold` variable normally distributed? Provide both visual (histogram and QQ-plot) and numeric (Shapiro-Wilk test and skewness/kurtosis values) support for your answer.

```
# Calculate mean and standard deviation of breathhold data
mean_breathhold <- mean(data$breathhold, na.rm = TRUE)
sd_breathhold <- sd(data$breathhold, na.rm = TRUE)
```

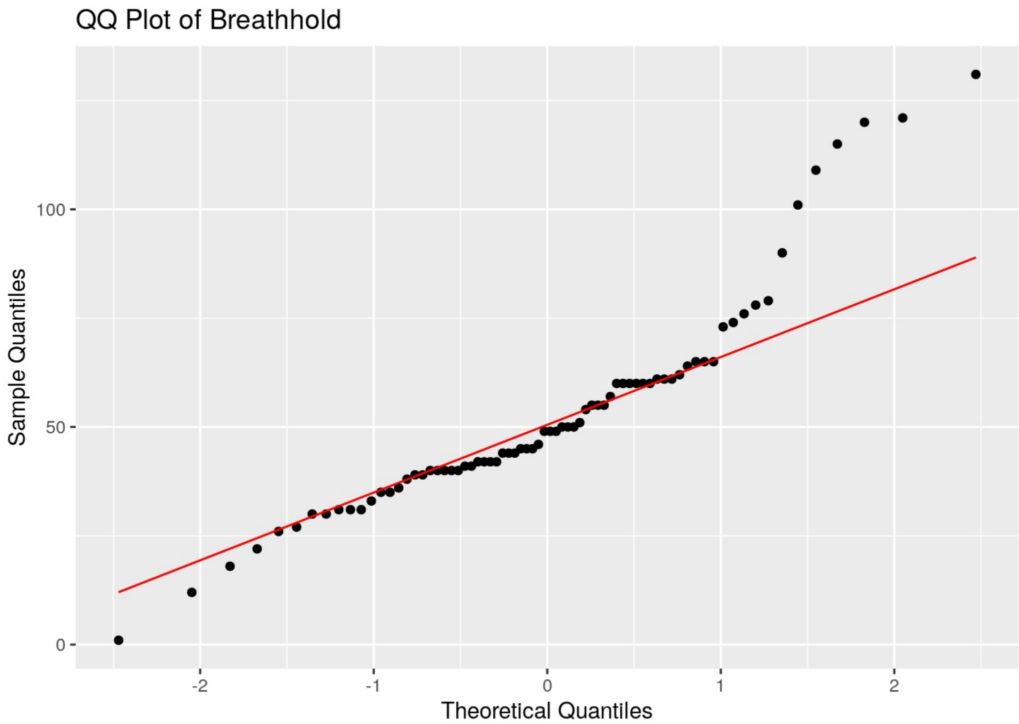
```
# Create Histogram
hist_plot <- ggplot(data, aes(x = breathhold)) +
  geom_histogram(binwidth = 0.5, fill = 'skyblue', color = 'black') +
  labs(title = "Histogram of Breathhold", x = "Breathhold", y = "Frequency")
hist_plot
```



From our histogram, we can observe somewhat of a tendency around 45, where data seems to cluster around. There might be signs of normality in data, but the signals are not that clear.

Now I will continue with the qq-plot. Plotting quantiles against quantiles is a common technique in statistical analysis to visualize how the interact.

```
# I am plotting  QQ-Plot using ggplot2
ggplot(data, aes(sample = breathhold)) +
  stat_qq() +
  stat_qq_line(color = "red") +
  labs(title = "QQ Plot of Breathhold", x = "Theoretical Quantiles", y = "Sample Quantiles")
```



Here we are seeing the same trend, where we have outliers.

Now we perform statistical test, and beforehand it is always important, clarify what hypothesis we are testing.

Lad X være fordeling af breathhold stoch. var:

$$H_0 : X \sim N(\mu, \sigma)$$

and the alternative hypothesis

$$H_1 : \neg(X \sim N(\mu, \sigma))$$

We perform the test:

```
# Perform Shapiro-Wilk normality test
shapiro_test <- shapiro.test(data$breathhold)

# Print test result
shapiro_test
```

```
##
##  Shapiro-Wilk normality test
##
## data:  data$breathhold
## W = 0.9001, p-value = 2.445e-05
```

Based on our test statistic, W, we recieve a very critical p-value. That means, that if we are in the scenario of the null hyp. we would be very suprised by this observation. Therefore, it is highly unlikely, that we will be seeing this result. By that we might infer, that the null hypothesis, that data is normal, is highly unlikely by this observation. So therefore, we are forced to reject, and by the law of excluded middle in this binary setup:

$$H_0 \vee H_1 = T$$

In conclusion, we have a critical p-value, therefore we must reject H_0 and since we have a binary setup, we must then accept H_1.

For the moments:

```
# Mean
mean_breathhold <- mean(data$breathhold, na.rm = TRUE)

# Variance
variance_breathhold <- var(data$breathhold, na.rm = TRUE)

# Skewness (Manual calculation)
n_breathhold <- sum(!is.na(data$breathhold))  # Number of non-NA values
mean_diff_breathhold <- data$breathhold - mean_breathhold
skewness_breathhold <- (n_breathhold / ((n_breathhold - 1) * (n_breathhold - 2))) * sum((mean_diff_breathhold^3),
na.rm = TRUE) / (sd(data$breathhold, na.rm = TRUE)^3)

# Kurtosis (Manual calculation)
kurtosis_breathhold <- ((n_breathhold * (n_breathhold + 1)) / ((n_breathhold - 1) * (n_breathhold - 2) * (n_breat
hhold - 3))) * sum((mean_diff_breathhold^4), na.rm = TRUE) / (sd(data$breathhold, na.rm = TRUE)^4) - (3 * (n_brea
thhold - 1)^2 / ((n_breathhold - 2) * (n_breathhold - 3)))

# Print the results
mean_breathhold
```

```
## [1] 53.13514
```

```
variance_breathhold
```

```
## [1] 606.6938
```

```
skewness_breathhold
```

```
## [1] 1.212791
```

```
kurtosis_breathhold
```

```
## [1] 2.000276
```

The breathhold data can be evaluated for normality using the following results from the moments calculation:

- The mean is 53.13, which represents the central tendency of the data.
- The variance is 606.69, indicating a relatively high spread in the breathhold times.

Skewness is 1.21, which is positive and indicates that the data is moderately skewed to the right, meaning there are more data points concentrated on the lower side, with some higher values pulling the tail to the right. For a normal distribution, skewness should be close to 0, so this suggests some deviation from normality.

Kurtosis is 2.00, which is slightly below 3 (the kurtosis of a normal distribution). This indicates that the distribution has lighter tails than normal, meaning there are fewer extreme values than would be expected in a normal distribution.

In summary, the positive skewness and lower kurtosis suggest that the breathhold data is not perfectly normally distributed. The data is moderately right-skewed with lighter tails than a normal distribution.

####Conclusion on breathhold

In conclusion, I reflect, that the visuals were a bit deceiving to my understanding of data, that by the test, seems to be very far from normal. This is likely due to extreme outliers or irregularities in the data.

This finding is quite interesting and highlights some essential statistical questions of visual representations as a deceiving interpretation.

Question 5

Are the two balloon reaction time variables (`balloon` and `balloon_balance`) normally distributed? Provide visual (histogram and QQ-plot) and numeric (Shapiro-Wilk test and skewness/kurtosis values) support for your answer.

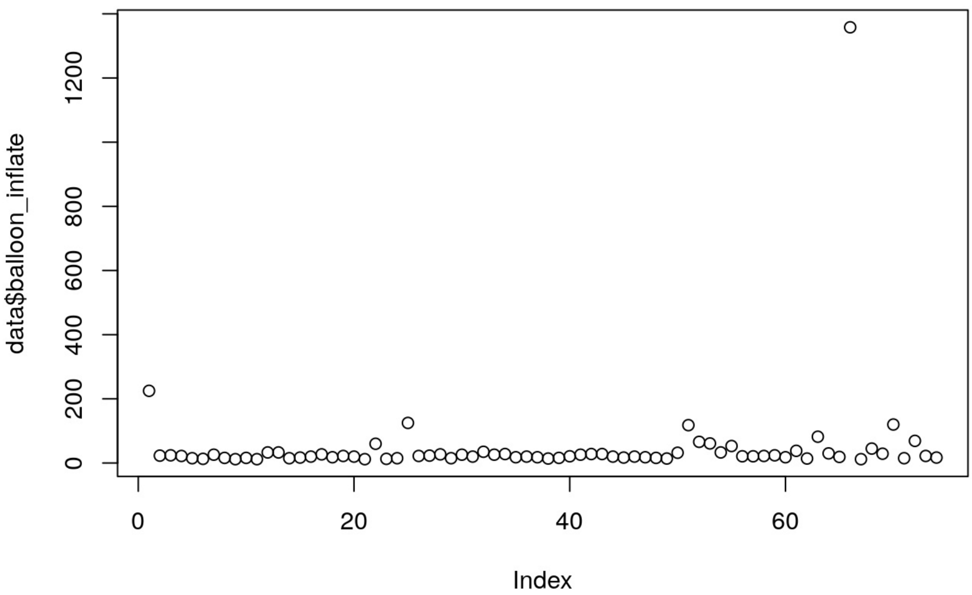
If they are not, then discuss your results below.

So, basically, I am repeating my methods from question 4 twice. First on the ballon variable. Then on the ballon_balance variable.

Ballon

Plotting

```
plot(data$balloon_inflate)
```



Noticing one heavy outlier:

```
max(data$balloon_inflate)
```

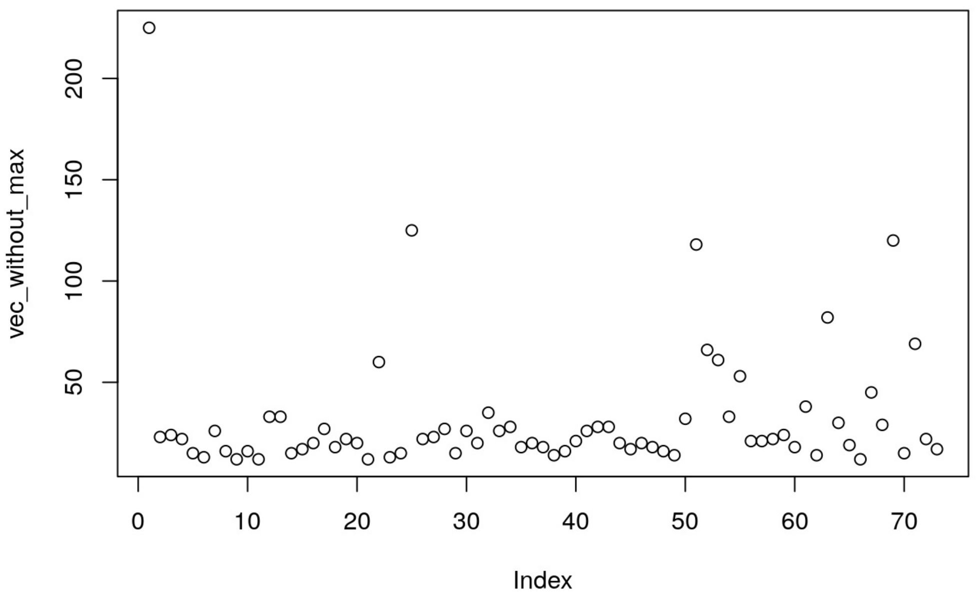
```
## [1] 1358
```

This is a unrealistic value. It should be removed for further analysis:

```
# Remove the maximum value
vec_without_max <- data$balloon_inflate[data$balloon_inflate != max(data$balloon_inflate)]
```

Now plotting

```
plot(vec_without_max)
```



And now the data looks better and more realistic, considering the actual task of inflating a balloon.

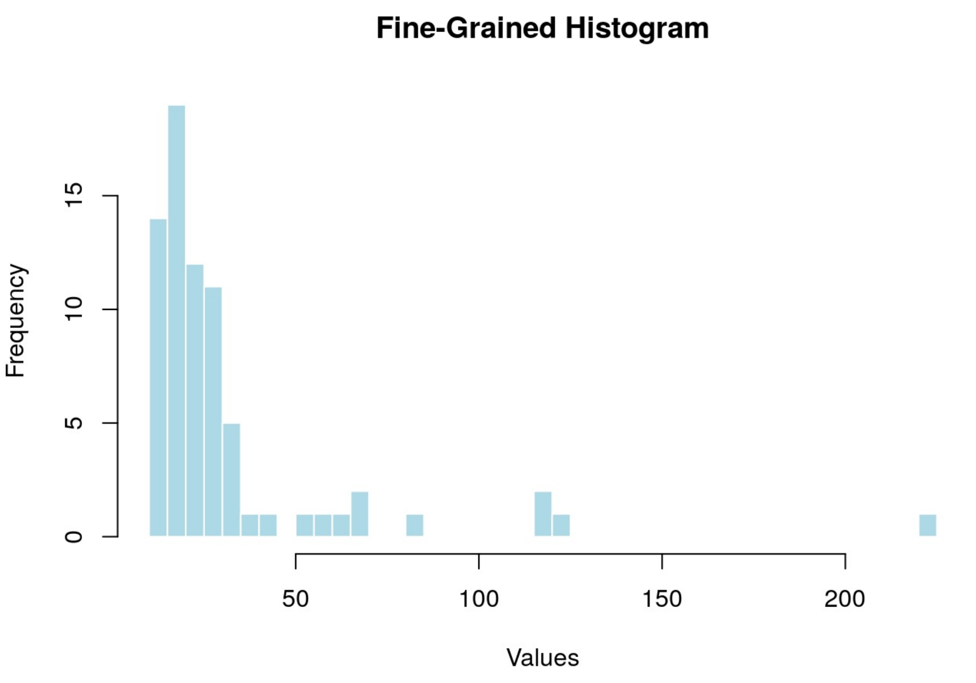
This is an example, that data cleaning and scraping is an important part of proper statistical analysis and data science.

Visualizing with a histogram

```
length(vec_without_max)
```

```
## [1] 73
```

```
hist(
  vec_without_max,
  breaks = 50,        # Increase the number of breaks to refine granularity
  col = "lightblue", # Optional aesthetic improvements
  main = "Fine-Grained Histogram",
  xlab = "Values",
  border = "white"
)
```

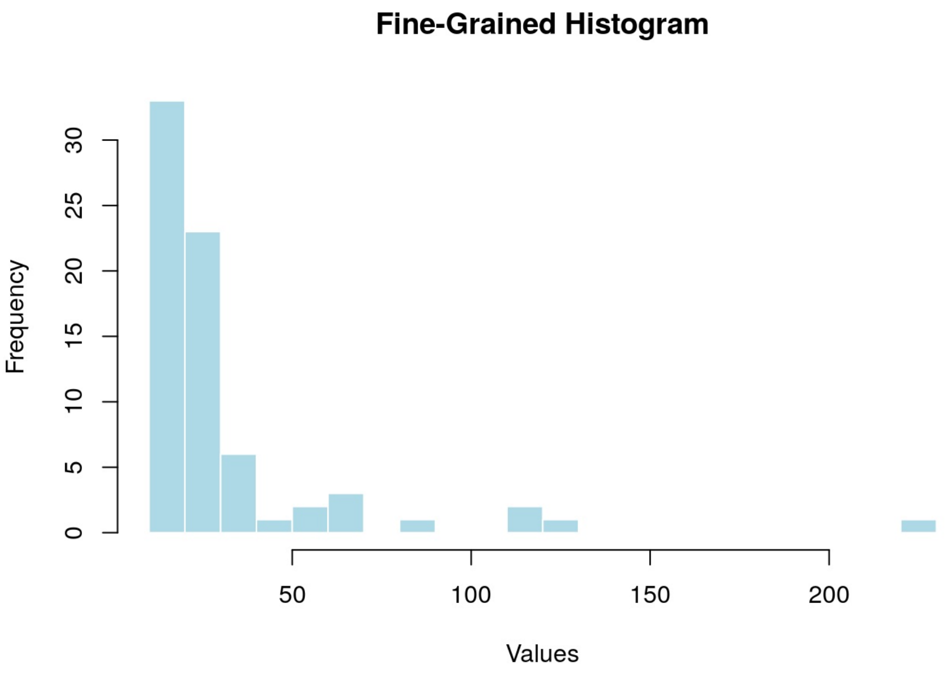


Now I have a vector that is cleaned, but this is not optimal, since i want to work with the shoesizes, therefore I create a corrected dataframe:

```
# Creating a numeric vector without the outlier
vec_without_max <- data$balloon_inflate[data$balloon_inflate != max(data$balloon_inflate)]

# Removing the row with the outlier (assuming participant ID = 66)
data_clean <- data[data$ID != 66, ]
data_clean
```

```
## # A tibble: 73 × 47
##       ID shoesize gender native_Danish handedness   choose_rand_num touch_floor
##    <dbl>    <dbl> <chr>  <chr>         <chr>                  <dbl> <chr>
##  1     1       43 male   No            Right-handed               9 Option 3
##  2     2       41 male   No            Right-handed               9 Option 4
##  3     3       45 male   Yes           Right-handed               1 Option 2
##  4     4       43 male   Yes           Right-handed               7 Option 2
##  5     5       41 male   Yes           Right-handed               3 Option 2
##  6     6       44 male   Yes           Right-handed              10 Option 2
##  7     7       41 female Yes           Right-handed               4 Option 1
##  8     8       43 female Yes           Left-handed                2 Option 2
##  9     9       44 male   Yes           Right-handed               7 Option 5
## 10    10       36 female Yes           Right-handed               4 Option 1
## # ℹ 63 more rows
## # ℹ 40 more variables: hands_touch_behind_back <chr>, `2D4D` <chr>,
## #   balloon_inflate <dbl>, balloon_balance <dbl>, breathhold <dbl>,
## #   bad_choices <chr>, tongue_twist <dbl>, romberg_open <dbl>,
## #   romberg_closed <dbl>, ling_animal <chr>, ling_direct <chr>,
## #   ling_demonstr <chr>, ling_place <chr>, ling_abstract <chr>,
## #   ling_pronoun <chr>, ling_math <chr>, ling_activity <chr>, …
```

```
# Adjusting the histogram to make it more fine-grained
hist(
  data_clean$balloon_inflate,
  breaks = 20,        # Increase the number of breaks to refine granularity
  col = "lightblue", # Optional aesthetic improvements
  main = "Fine-Grained Histogram",
  xlab = "Values",
  border = "white"
)
```



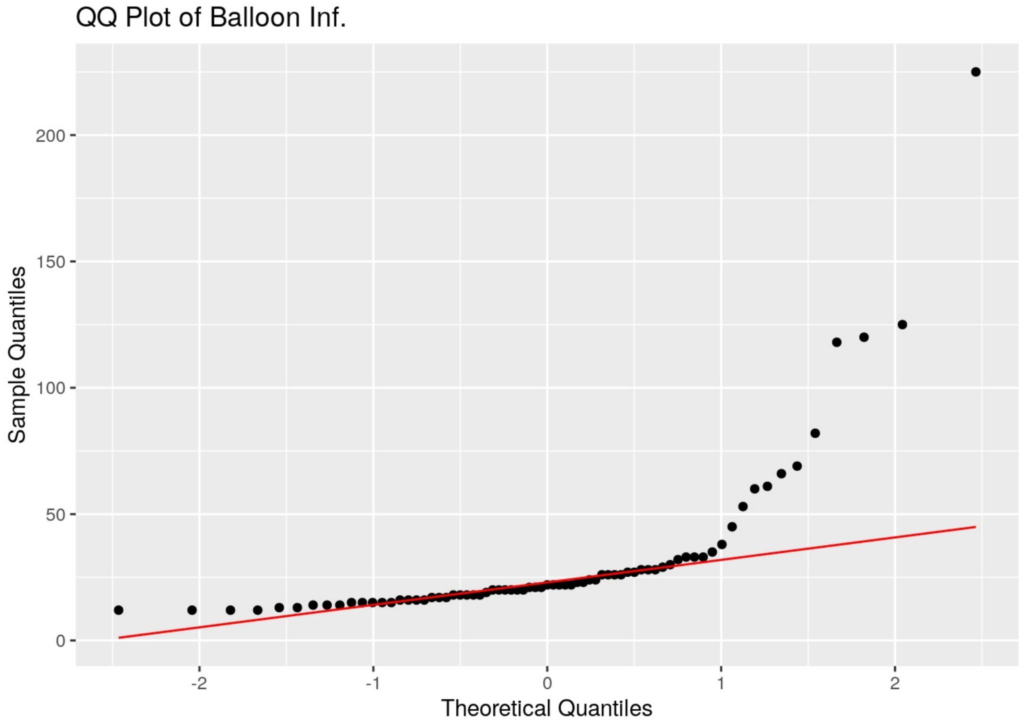
Calculating summary;

```
# Calculate mean and standard deviation of breathhold data

mean_ballon <- mean(data_clean$balloon_inflate, na.rm = TRUE)
sd_ballon <- sd(data_clean$balloon_inflate, na.rm = TRUE)

print(c(mean_ballon,sd_ballon))
```

```
## [1] 31.93151 32.95718
```

Now the qq-plot:

```
# I am plotting  QQ-Plot using ggplot2
ggplot(data_clean, aes(sample = balloon_inflate)) +
  stat_qq() +
  stat_qq_line(color = "red") +
  labs(title = "QQ Plot of Balloon Inf.", x = "Theoretical Quantiles", y = "Sample Quantiles")
```



The same picture is drawn. Data looks pretty normal without the outlier.

Now for the numeric assesment, the SW test:

```
# Shapiro-Wilk Test for normality
shapiro_test <- shapiro.test(data_clean$balloon_inflate)
shapiro_test
```

```
##
##  Shapiro-Wilk normality test
##
## data:  data_clean$balloon_inflate
## W = 0.54375, p-value = 1.033e-13
```

Even though we removed the extreme outlier over 1000, the p-value is extremely critical, we must reject H_0 and by LEM accept H_1.

The moments:

```
# Mean
mean_inflate <- mean(data_clean$balloon_inflate, na.rm = TRUE)

# Variance
variance_inflate <- var(data_clean$balloon_inflate, na.rm = TRUE)

# Skewness (Manual calculation)
n_inflate <- sum(!is.na(data_clean$balloon_inflate))  # Number of non-NA values
mean_diff_inflate <- data_clean$balloon_inflate - mean_inflate
skewness_inflate <- (n_inflate / ((n_inflate - 1) * (n_inflate - 2))) * sum((mean_diff_inflate^3), na.rm = TRUE)
/ (sd(data_clean$balloon_inflate, na.rm = TRUE)^3)

# Kurtosis (Manual calculation)
kurtosis_inflate <- ((n_inflate * (n_inflate + 1)) / ((n_inflate - 1) * (n_inflate - 2) * (n_inflate - 3))) * sum
((mean_diff_inflate^4), na.rm = TRUE) / (sd(data_clean$balloon_inflate, na.rm = TRUE)^4) - (3 * (n_inflate - 1)^2
/ ((n_inflate - 2) * (n_inflate - 3)))

# Print the results
mean_inflate
```

```
## [1] 31.93151
```

```
variance_inflate
```

```
## [1] 1086.176
```

```
skewness_inflate
```

```
## [1] 3.768413
```

```
kurtosis_inflate
```

```
## [1] 17.25535
```

The mean is 31.93151, which represents the central tendency of the data. The variance is 1086.176, indicating a very high spread in the balloon inflate values.

Skewness is 8.07, which is highly positive, indicating a very strong right skew. This means that most of the data points are concentrated on the lower side, with a few very large values pulling the tail significantly to the right. This is probably our significant oulier promoting this tendency. For a normal distribution, skewness should be close to 0, so this skewness suggests a strong deviation from normality.

Kurtosis is 17.25535, which is much higher than 3 (the kurtosis of a normal distribution). This indicates that the distribution has extremely heavy tails, meaning there are many extreme values far from the mean. Such a high kurtosis is a clear indicator that the data deviates strongly from a normal distribution.

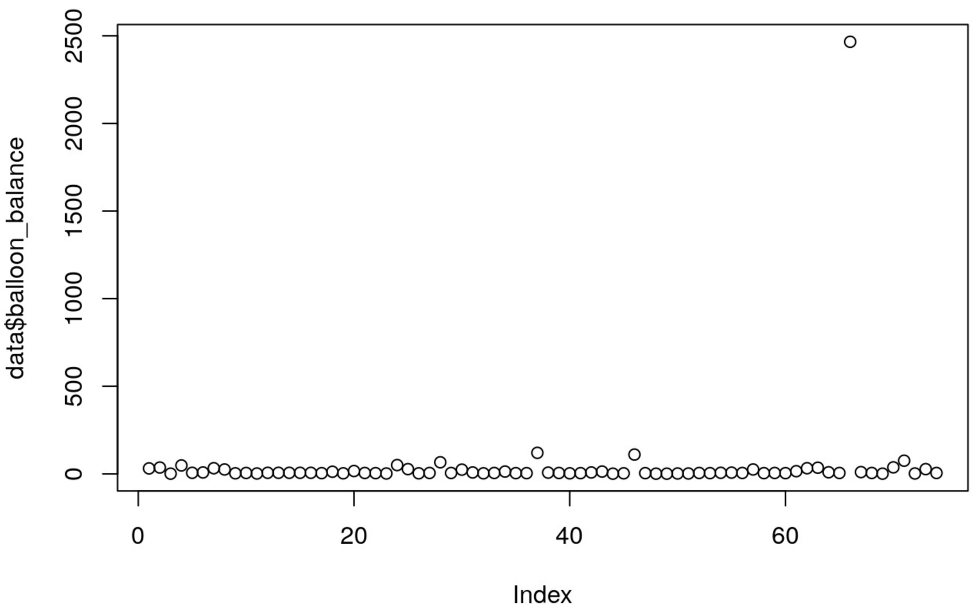
The very high positive skewness and extreme kurtosis suggest that the balloon inflate data is far from normally distributed. The data shows strong right-skew and a high number of extreme values.

Balloon Balance

Repeating the same procedure:

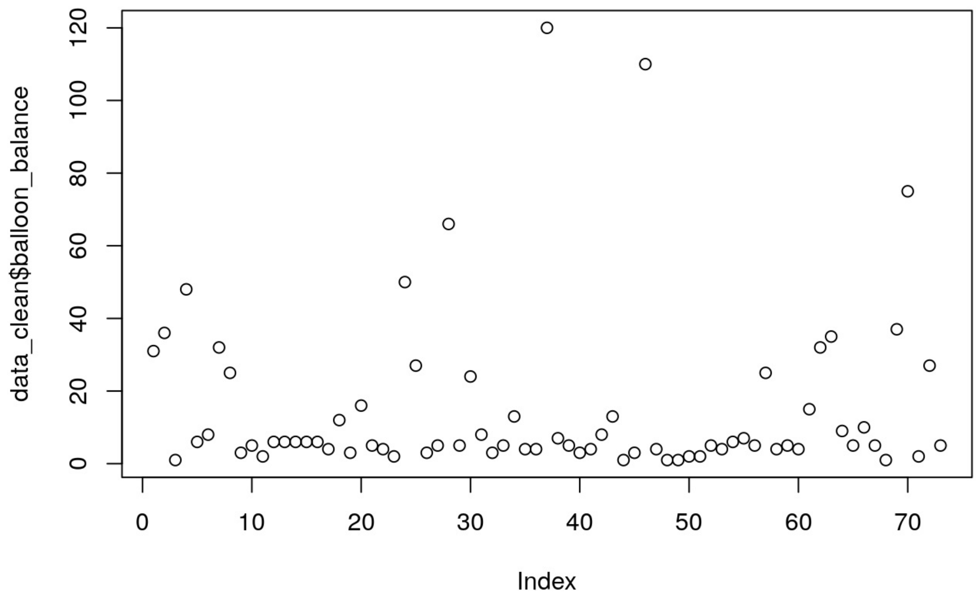
Plotting for overview:

```
plot(data$balloon_balance)
```



Same story. We have a unrealistic outlier. It has been removed in data_clean:

```
plot(data_clean$balloon_balance)
```

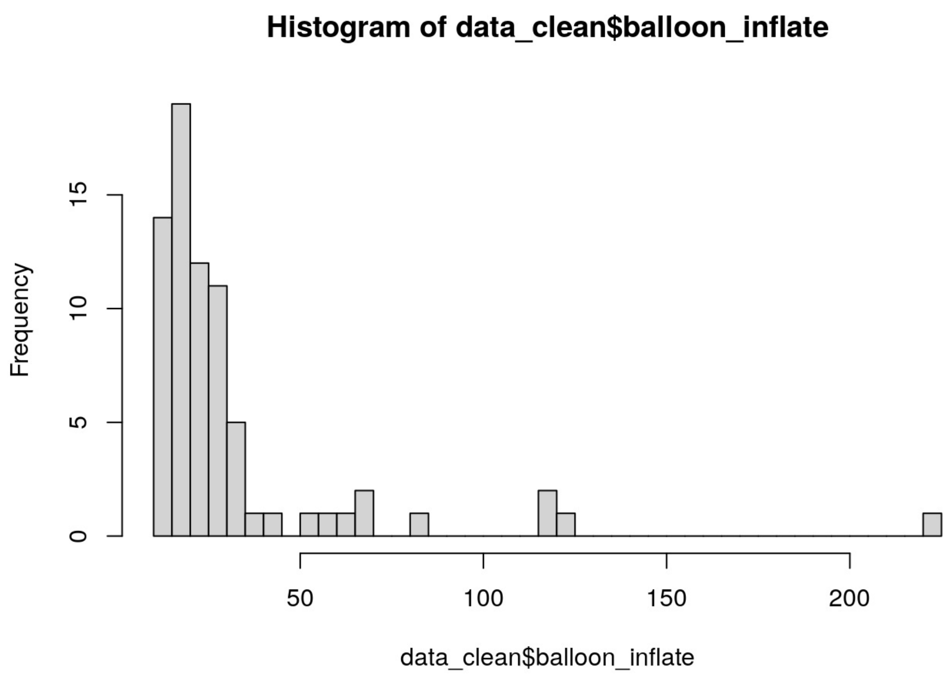



```
# Calculate mean and standard deviation of breathhold data

mean_ballon_balance <- mean(data_clean$balloon_balance, na.rm = TRUE)
sd_ballon_balance <- sd(data_clean$balloon_balance, na.rm = TRUE)
print(c(mean_ballon_balance,sd_ballon_balance))
```

```
## [1] 15.02740 22.72784
```

Histogram:

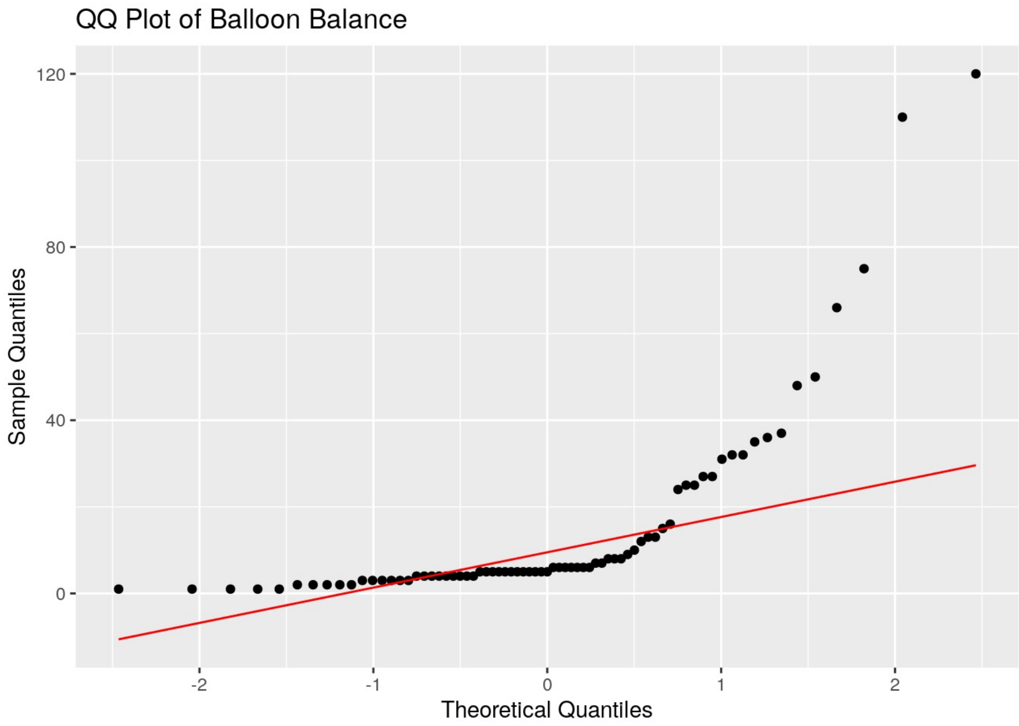
```
# Create Histogram
hist(data_clean$balloon_inflate, breaks=50)
```



We see an improvement since removing the extreme outlier over 200.

With qq-plot:

```
# I am plotting QQ-Plot using ggplot2
ggplot(data_clean, aes(sample = balloon_balance)) +
  stat_qq() +
  stat_qq_line(color = "red") +
  labs(title = "QQ Plot of Balloon Balance", x = "Theoretical Quantiles", y = "Sample Quantiles")
```



And for the test:

```
# Shapiro-Wilk Test for normality
shapiro_test <- shapiro.test(data_clean$balloon_balance)
shapiro_test
```

```
##
##  Shapiro-Wilk normality test
##
## data:  data_clean$balloon_balance
## W = 0.6002, p-value = 8.538e-13
```

Rejecting H_0 due to significantly critical results.

The moments:

```
# Mean
mean_balance <- mean(data_clean$balloon_balance, na.rm = TRUE)

# Variance
variance_balance <- var(data_clean$balloon_balance, na.rm = TRUE)

# Skewness (Manual calculation)
n <- sum(!is.na(data_clean$balloon_balance))  # Number of non-NA values
mean_diff <- data_clean$balloon_balance - mean_balance
skewness_balance <- (n / ((n - 1) * (n - 2))) * sum((mean_diff^3), na.rm = TRUE) / (sd(data_clean$balloon_balance
, na.rm = TRUE)^3)

# Kurtosis (Manual calculation)
kurtosis_balance <- ((n * (n + 1)) / ((n - 1) * (n - 2) * (n - 3))) * sum((mean_diff^4), na.rm = TRUE) / (sd(data
_clean$balloon_balance, na.rm = TRUE)^4) - (3 * (n - 1)^2 / ((n - 2) * (n - 3)))

# Print the results
mean_balance
```

```
## [1] 15.0274
```

```
variance_balance
```

```
## [1] 516.5548
```

```
skewness_balance
```

```
## [1] 2.94457
```

```
kurtosis_balance
```

```
## [1] 9.702921
```

The mean is 15.0274, which represents the central tendency of the data. The variance is 516.5548, indicating a very high spread in the balloon inflate values.

Skewness is 2.94457, which is positive, indicating a strong right skew. This means that most of the data points are concentrated on the lower side, with a few very large values pulling the tail significantly to the right. This is probably our significant oulier promoting this tendency. For a normal distribution, skewness should be close to 0, so this skewness suggests a strong deviation from normality.

Kurtosis is 9.702921, which is much higher than 3 (the kurtosis of a normal distribution). This indicates that the distribution has extremely heavy tails, meaning there are many extreme values far from the mean. Such a high kurtosis is a clear indicator that the data deviates strongly from a normal distribution.

The very high positive skewness and extreme kurtosis suggest that the balloon inflate data is far from normally distributed. The data shows strong right-skew and a high number of extreme values.

Explain your results in plain terms here (max 3 sentences):

I think that the analysis done with the ballon data was quite unneccesary from the moment one observes the extreme outleir. It provides some very extreme numerical measures, that does not represent the nature of our sample.

Therefore, the updated analysis, where the outliers was removed was much better. That being said, the tests yielded no different results.

Lastly, I conclude, that the relevants analysis, visualizations and interpretations have been demonstrated.

The first assignment is hereby concluded by Søren Emil Skaarup, CogSci 2024.

Loading [MathJax]/jax/output/HTML-CSS/fonts/TeX/fontdata.js

Portfolio Exam - Part 2 | Methods 1 F24, CogSci @AU

Sofie Knudsen, Søren Emil Skaarup, Asger Øllgaard

2024-11-1

The code has been made in the group: Sofie Knudsen, Søren Emil Skaarup, and Asger Øllgaard.

Loading packages:

```
library("tidyverse")
library("pastecs")
library("WRS2")
library("conflicted")
library("readr")
library("readxl")
library("ggplot2")
```

Loading in the data and reducing the number of decimals:

```
# Made by Asger
Readingsdata <- read_excel("/work/CogSci_Methods01/portfolio-assignment02-e24-asgerollgaard/Readingsdata.xlsx")

wordfrequency <- read_excel("/work/CogSci_Methods01/portfolio-assignment02-e24-asgerollgaard/wordfrequency.xls")

data<-Readingsdata

# keeping an extra dataframe for later use in the hypotheses testing section.
hdata<-Readingsdata

data$ReactionTime<-as.numeric(data$ReactionTime)
```

Applying column names:

```
# Made by Sofie
colnames(data)<-c("ID","Age","Gender","Condition","ReactionTime","Word")

# Removing the data for the incongruent word "volcano" and the corresponding congruent word "chair".
data <- data %>%
  dplyr::filter(Word != "volcano," & Word != "chair,")
```

Assigning random numbers to ID:

```
# Made by Søren
data <- data %>%
  group_by(ID) %>%
  mutate(ID = round(runif(1, min = 0, max = 1), 4))
```

Part 2.1: Correlations

Word length analysis

First, we compute the number of the characters in each word. Then we test both reaction time and word length for normality with Shapiro-Wilks test:

```
# Made by Asger
# Adding a column with the number of characters in each word and removing punctuation
data <- data %>%
  mutate(
    cleaned_words = str_remove_all(Word, "[[:punct:]]"),
    characters = nchar(cleaned_words))

# Making the words lowercase for consistency
data$cleaned_words <- tolower(data$cleaned_words)

# Testing for normality
print(c(shapiro.test(data$characters)[2], shapiro.test(data$ReactionTime)[2]))
```

```
## $p.value
## [1] 3.535586e-34
##
## $p.value
## [1] 4.951221e-43
```

From Shapiro-Wilks test, we can conclude that the data is not normal, since the p-values are below 0.05. Therefore, we perform log transformations on the data and then compute the correlation with the Pearson method.

```
# Made by Sofie
# Log transforming the data
cha_log<- log(data$characters)
rt_log<- log(data$ReactionTime)

# Testing for normality
print(shapiro.test(cha_log))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  cha_log
## W = 0.94575, p-value < 2.2e-16
```

```
print(shapiro.test(rt_log))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  rt_log
## W = 0.99311, p-value = 2.262e-09
```

Even with log transformations in the Shapiro-Wilks test, there is still no normality. Therefore, we will try to make a non-parametric correlation test.

```
# Made by Sofie
# Doing a non-parametric correlation test
print(cor.test(data$characters,data$ReactionTime, method="spearman"))
```

```
##
##  Spearman's rank correlation rho
##
## data:  data$characters and data$ReactionTime
## S = 2321239377, p-value = 0.001382
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##        rho
## 0.06445231
```

Since the p-value is below 0.05, we can conclude that there is a significant correlation between word length and reaction time.

Word frequency analysis

We add the word frequency data into the data frame and compute the correlation:

```
# Made by Søren
# Adding word frequency data
wordfrequency <- as.data.frame(wordfrequency) %>%
  select(1:2)

# Making the word frequency data numeric
wordfrequency$FREQcount <- as.numeric(wordfrequency$FREQcount)

# Making the words lowercase
wordfrequency$Word <- tolower(wordfrequency$Word)

# Joining the data frames
data <- data %>%
  left_join(wordfrequency, by = c("cleaned_words" = "Word"))

# Testing for normality
print(shapiro.test(data$FREQcount))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  data$FREQcount
## W = 0.6778, p-value < 2.2e-16
```

```
print(shapiro.test(data$ReactionTime))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  data$ReactionTime
## W = 0.85338, p-value < 2.2e-16
```

We are seeing that the data is not normal. Therefore, we will try to make a non-parametric correlation test.

```
# Made by Søren
# Doing a non-parametric correlation test
print(cor.test(data$FREQcount,data$ReactionTime, method="spearman"))
```

```
##
##  Spearman's rank correlation rho
##
## data:  data$FREQcount and data$ReactionTime
## S = 2596892976, p-value = 0.02069
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##         rho
## -0.04664657
```

Since the p-value is equals to 0.02, we can conclude that there is a significant correlation between word frequency and reaction time.

Ordinal word number analysis

First, we compute the ordinal word number in each sentence in the text. To do this, we count the number of words in each sentence and assign an ordinal number to each word.

```
# Made by Asger
ordinal_counter <- 0

ordinal_word_number <- integer(length(data$Word))

# Here we loop through the data and count the ordinal word number in each sentence and assign it to the data
for (i in seq_along(data$Word)) {
  if (grepl("\\.", data$Word[i])) {
    ordinal_counter <- 0
  } else {
    ordinal_counter <- ordinal_counter + 1
  }
  ordinal_word_number[i] <- ordinal_counter
}

# Assigning a new data column with the ordinal word number
data$ordinal_word_number <- ordinal_word_number

# Replacing the 0 values with the previous value + 1
data$ordinal_word_number <- ifelse(data$ordinal_word_number == 0,
                                   dplyr::lag(data$ordinal_word_number) + 1,
                                   data$ordinal_word_number)
```

Now, we have the two variables we want to run Pearson's correlation on. Before finding the correlation coefficient, we check for normality:

```
# Made by Søren
# making a sharpiro test for the ordinal word number
print(shapiro.test(data$ordinal_word_number))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  data$ordinal_word_number
## W = 0.95339, p-value < 2.2e-16
```

```
print(shapiro.test(data$ReactionTime))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  data$ReactionTime
## W = 0.85338, p-value < 2.2e-16
```

```
# since the data is not normal, we log transform the data
own_log<- log(data$ordinal_word_number)
own2_log<- log(data$ReactionTime)

# making a shapiro test for the log transformed data
print(shapiro.test(own_log))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  own_log
## W = 0.92069, p-value < 2.2e-16
```

```
print(shapiro.test(own2_log))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  own2_log
## W = 0.99311, p-value = 2.262e-09
```

```
# since there is still no normality, we will try to make a non-parametric correlation test
print(cor.test(data$ordinal_word_number,data$ReactionTime,method="spearman"))
```

```
##
##  Spearman's rank correlation rho
##
## data:  data$ordinal_word_number and data$ReactionTime
## S = 2612376505, p-value = 0.0087
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##         rho
## -0.05288702
```

Since the p-value is 0.0087 we can conclude that there is a significant correlation between ordinal word number and reaction time.

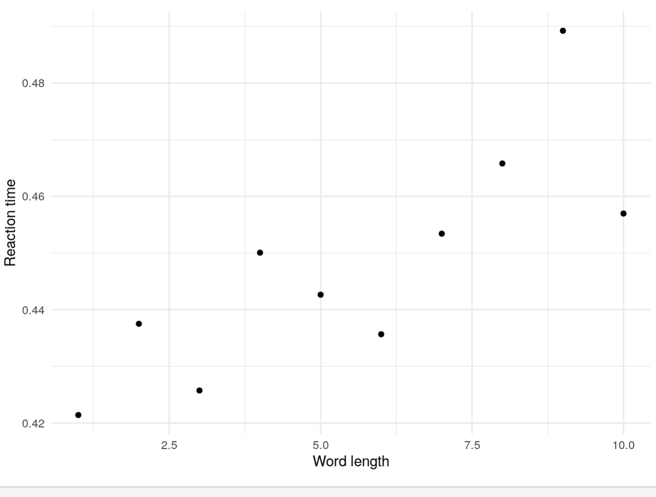
The correlation analysis on reaction time across variables like word length, frequency, and ordinal word position reveals significant relationships, indicating that these characteristics influence reaction times in this dataset. First, we calculated the number of characters for each word and checked reaction time and word length for normality. The Shapiro-Wilk test results indicated non-normal distributions, so we log-transformed the data. After transformation, the data insufficiently approximated normality, allowing us to proceed with a Spearman's correlation analysis. The resulting correlation between word length and reaction time was negative and significant ($p < 0.05$), suggesting longer words are correlated with slower reaction times.

Next, we incorporated word frequency data and examined its relationship with reaction time. This analysis also revealed a significant negative correlation ($p < 0.05$), indicating that more frequent words are associated with faster reaction times. Finally, we analyzed ordinal word position (i.e., each word's position within the sentence). After testing for normality and applying Spearman's correlation, we found a significant negative relationship ($p < 0.05$), suggesting that later words in a sentence are processed more quickly.

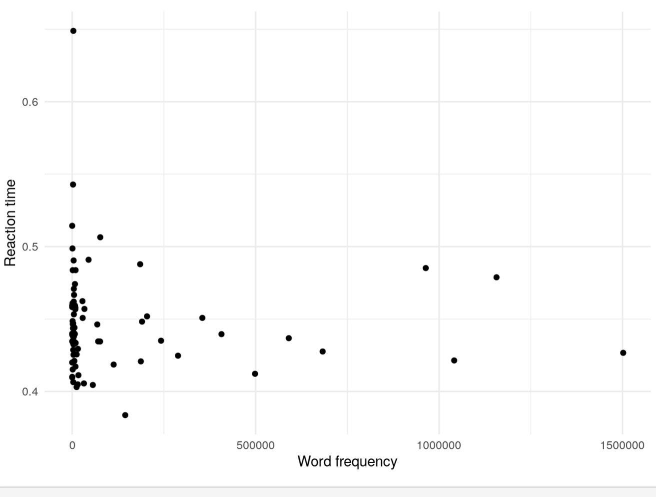
These findings suggest that the studied variables — word length, frequency, and ordinal word position — significantly influence reaction times. Specifically, longer words slow reaction times, higher word frequency facilitates faster reaction time, and later word positions are associated with faster reaction times.

Relevant plots from the conclusion are shown below:

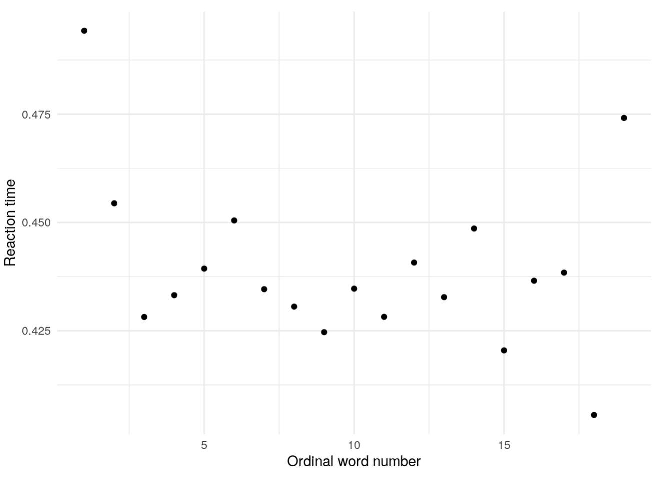
```
# Made by Asger
# Finding the median for each reaction time for word length
median_reaction_time1 <- data %>%
  group_by(characters) %>%
  summarise(median_reaction_time = median(ReactionTime))

# Finding the median for each reaction time for word frequency
median_reaction_time2 <- data %>%
  group_by(FREQcount) %>%
  summarise(median_reaction_time = median(ReactionTime))

# Finding the median for each reaction time for ordinal word number
median_reaction_time3 <- data %>%
  group_by(ordinal_word_number) %>%
  summarise(median_reaction_time = median(ReactionTime))

# Scatterplot between reaction time and word length median
median_reaction_time1 %>%  ggplot(aes(x = characters, y = median_reaction_time)) +
  geom_point() +
  labs(x = "Word length", y = "Reaction time") +
  theme_minimal()
```




```
# Scatterplot between reaction time and word frequency
median_reaction_time2 %>%  ggplot(aes(x = FREQcount, y = median_reaction_time)) +
  geom_point() +
  labs(x = "Word frequency", y = "Reaction time") +
  theme_minimal()
```




```
# Scatterplot between reaction time and ordinal word number
median_reaction_time3 %>%  ggplot(aes(x = ordinal_word_number, y = median_reaction_time)) +
  geom_point() +
  labs(x = "Ordinal word number", y = "Reaction time") +
  theme_minimal()
```



Part 2.2: Hypothesis testing

First, we find the means of the reaction times for the two words "volcano" and "chair":

```
# Made by Asger

data_incon<- hdata %>%
    dplyr::filter(Word=="volcano," | Word=="chair,")

# Making a new data frame with only the word "volcano"
volcanodata<-data_incon %>%
    dplyr::filter(Word=="volcano,")

print(mean(as.numeric(volcanodata$ReactionTime)))
```

```
## [1] 0.5904665
```

```
# Making a new data frame with only the word "chair"
chairdata<-data_incon %>%
    dplyr::filter(Word=="chair,")

print(mean(as.numeric(chairdata$ReactionTime)))
```

```
## [1] 0.492647
```

In order to check if the data is normal, we will perform a Shapiro-Wilks test:

```
# Made by Sofie
# shapiro test for the reaction times for the word "volcano"
shapiro.test(as.numeric(volcanodata$ReactionTime))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  as.numeric(volcanodata$ReactionTime)
## W = 0.69996, p-value = 0.0008419
```

```
#shapiro test for the reaction times for the word "chair"
shapiro.test(as.numeric(chairdata$ReactionTime))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  as.numeric(chairdata$ReactionTime)
## W = 0.91919, p-value = 0.4233
```

```
# log transforming the data
log_volcano<-log(as.numeric(volcanodata$ReactionTime))

# log transforming the data
log_chair<-log(as.numeric(chairdata$ReactionTime))

# two-sample t-test
t.test((log_volcano), (log_chair))
```

```
##
##  Welch Two Sample t-test
##
## data:  (log_volcano) and (log_chair)
## t = 0.55267, df = 17.684, p-value = 0.5874
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.3021757  0.5175332
## sample estimates:
##  mean of x  mean of y
## -0.6619327 -0.7696115
```

Since the p-value is 0.5874 we can conclude that there is no significant difference between the reaction times for the two words.

We will now investigate the means between the following words after the incongruent and congruent words. First, we find the means.

```
# Made by Søren
# new data frame with only the word "listening"
foldata<-data %>%
  dplyr::filter(Word=="listening")

# filter the data for the word "listening" after the congruent word
foldata0<-foldata %>%
  dplyr::filter(Condition=="0")

# filter the data for the word "listening" after the incongruent word
foldata1<-foldata %>%
  dplyr::filter(Condition=="1")

# finding the mean of the reaction times for the word "listening" after the congruent word
print(mean(as.numeric(foldata0$ReactionTime)))
```

```
## [1] 0.4908687
```

```
# finding the mean of the reaction times for the word "listening" after the incongruent word
print(mean(as.numeric(foldata1$ReactionTime)))
```

```
## [1] 0.7591604
```

We are seeing the two means of the reaction times for the word "listening" after the congruent and incongruent words.

Before we perform a two-sample t-test, we will check if the data is normal with a Shapiro-Wilks test.

```
# Made by Asger
# Shapiro-Wilks test for the reaction times for the word "listening" after the congruent word
print(shapiro.test(as.numeric(foldata0$ReactionTime)))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  as.numeric(foldata0$ReactionTime)
## W = 0.94093, p-value = 0.6202
```

```
# Shapiro-Wilks test for the reaction times for the word "listening" after the incongruent word
print(shapiro.test(as.numeric(foldata1$ReactionTime)))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  as.numeric(foldata1$ReactionTime)
## W = 0.95212, p-value = 0.6682
```

Since the data is normal we can proceed with the two-sample t-test:

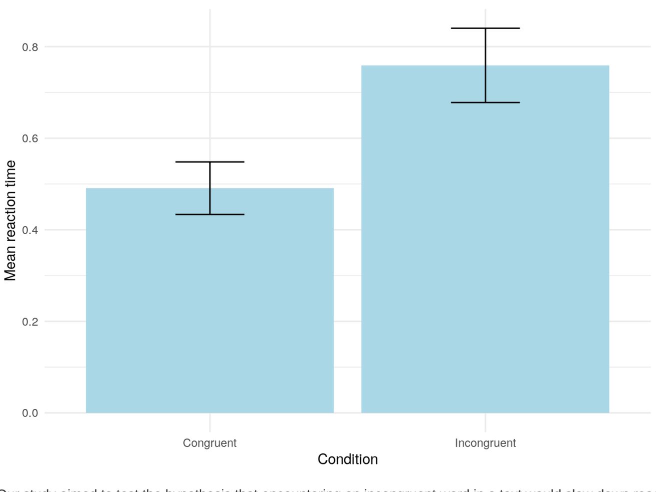
```
# Made by Asger
print(t.test(as.numeric(foldata0$ReactionTime), as.numeric(foldata1$ReactionTime)))
```

```
##
##  Welch Two Sample t-test
##
## data:  as.numeric(foldata0$ReactionTime) and as.numeric(foldata1$ReactionTime)
## t = -2.6997, df = 17.769, p-value = 0.01478
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.47727216 -0.05931134
## sample estimates:
## mean of x mean of y
## 0.4908687 0.7591604
```

Since the p-value is below 0.05, we can conclude that there is a significant difference between the reaction times for the word 'listening' after the congruent vs. the incongruent words.

Relevant plots from the conclusion are shown below:

```
# Made by Sofie
# Making a barplot of two bars indicating mean reaciton times word "listening" (the following word) in both condi
tions 1 and 0:
foldata0$Condition <- "Congruent"
foldata1$Condition <- "Incongruent"
foldata_all <- rbind(foldata0, foldata1)

foldata_all %>%
  ggplot(aes(x = Condition, y = ReactionTime)) +
  geom_bar(stat = "summary", fun = "mean", position = "dodge", fill = "lightblue") +
  geom_errorbar(stat = "summary", fun.data = "mean_se",
                position = position_dodge(width = 0.9), width = 0.25) +
  labs(x = "Condition", y = "Mean reaction time") +
  theme_minimal() +
  theme(legend.position = "none")
```



Our study aimed to test the hypothesis that encountering an incongruent word in a text would slow down reaction time on reading the word. To investigate this, we conducted t-tests comparing reading times across congruent and incongruent conditions. Specifically, we measured the difference in reading time between sentences containing congruent and incongruent words.

Our analysis revealed that the t-test between reading times for congruent and incongruent words yielded an insignificant result. This finding suggests that the presence of an incongruent word did not significantly impact the reading speed on the incongruent word itself compared to the congruent word. However, a second t-test comparing the reading speed of the word following the incongruent word to the same position following the congruent word showed a significant effect ($p < 0.05$).

These results indicate that the primary slowdown in reading occurs immediately after encountering an incongruent word, rather than on the incongruent word itself. This delay in processing on the subsequent word may reflect cognitive processing demands.

Thus, our findings highlight that reading comprehension is more significantly affected by the processing aftermath of incongruence than by the incongruence itself.

The python code for the experiment is provided below:

```
# File name: pythoncode02.py

# Importing necessary PsychoPy libraries
# Made by Søren Emil
from psychopy import visual, event, core, gui, data
import pandas as pd
import os

# Function to track the participant count and condition
# Made by Asger
def get_participant_count(filename="participant_count.txt"):
    """ Reads or initializes a participant count file and returns the count. """
    if os.path.exists(filename):
        with open(filename, 'r') as f:
            count = int(f.read())
    else:
        count = 0
    return count

def update_participant_count(count, filename="participant_count.txt"):
    """ Updates the participant count file. """
    with open(filename, 'w') as f:
        f.write(str(count))

# Getting the current participant count
# Made by Sofie
participant_count = get_participant_count()

# Participant Information
# Made by Sofie
exp_info = {'Participant': '', 'Age': '', 'Gender': ['Male', 'Female', 'Other']}
dlg = gui.DlgFromDict(exp_info)
if dlg.OK == False:
    core.quit()  # User pressed cancel

# Setting up the window
# Made by Søren Emil
win = visual.Window(fullscr=True, color='white')

# Creating a filename for data
# Made by Søren Emil
filename = f"data/{exp_info['Participant']}_reading_experiment"

# Control and experimental text
# Made by Søren Emil
control_text = "It was a quiet Tuesday afternoon, and Emma sat by the window, watching the rain. The soft tapping
of raindrops on the glass made a gentle sound. She held a warm cup of tea, feeling the heat in her hands. Outsid
e, the street looked shiny and wet. Cars drove by, splashing through puddles, and a few people hurried past, hold
ing umbrellas. Emma liked days like this. The rain seemed to make everything slow down. She picked up her book an
d curled up in the chair, listening to the rain. Even though it was just a normal afternoon, something about the
rain and the quiet made it feel special. Emma smiled as she read, feeling calm and happy, enjoying the simple pea
ce of the moment. "
experimental_text = "It was a quiet Tuesday afternoon, and Emma sat by the window, watching the rain. The soft ta
pping of raindrops on the glass made a gentle sound. She held a warm cup of tea, feeling the heat in her hands. O
utside, the street looked shiny and wet. Cars drove by, splashing through puddles, and a few people hurried past,
holding umbrellas. Emma liked days like this. The rain seemed to make everything slow down. She picked up her boo
k and curled up in the volcano, listening to the rain. Even though it was just a normal afternoon, something abou
t the rain and the quiet made it feel special. Emma smiled as she read, feeling calm and happy, enjoying the simp
le peace of the moment. "

# Splitting text into words
# Made by Søren Emil
control_words = control_text.split()
experimental_words = experimental_text.split()

# Alternate conditions: controlling for even count, experimental for odd
# Made by Søren Emil
if participant_count % 2 == 0:
    condition = 0  # Control
    words = control_words
else:
    condition = 1  # Experimental
    words = experimental_words

# Update the participant count
# Made by Asger
participant_count += 1
update_participant_count(participant_count)

#  Making clock to measure reading times
# Made by Asger
clock = core.Clock()

# Preparing a list to store the data
# Made by Asger
data_list = []

welcome_text = visual.TextStim(win, text="Welcome to our experiment. In the experiment you will be presented with
words as you tap on the space bar. Read the words out loud.           Press space to continue. ", color="black")
welcome_text.draw()
win.flip()
event.waitKeys(keyList=['space'])

# Instructions
# Made by Asger
instruction_text = visual.TextStim(win, text="Press space to start reading each word.", color='black')
instruction_text.draw()
win.flip()
event.waitKeys(keyList=['space'])

# Looping through each word and present it
# Made by Sofie
for i, word in enumerate(words):
    # Display the word
    word_stim = visual.TextStim(win, text=word, color='red')
    word_stim.draw()
    win.flip()

    # Start clock and wait for response
    clock.reset()
    event.waitKeys(keyList=['space'])

    # Record reading time
    reading_time = clock.getTime()

    # Append row data (consistent with example)
    data_list.append([exp_info['Participant'], exp_info['Age'], exp_info['Gender'], condition, reading_time, wor
d])

# Converting data to a pandas dataframe with appropriate column names
# Made by Søren Emil
df = pd.DataFrame(data_list, columns=['ID', 'Age', 'Gender', 'Condition', 'ReactionTime', 'Word'])

# Saving the data to a CSV file for each participant
# Made by Søren Emil
df.to_csv(f"{filename}_{condition}.csv", index=True)

# "Thank You" message
# Made by Søren Emil
thanks_text = visual.TextStim(win, text="Thank you for participating!", color='black')
thanks_text.draw()
win.flip()
core.wait(2)

# Window shutdown
# Made by Søren Emil
win.close()
core.quit()
```

Exploring Mental Rotation: Effects of Mirroring and Angular Disparity on Reaction Times

By Asger, Sofie & Søren Emil

Stage I Report

Assignment 03, Methods 01

Cognitive Science, 1st semester

Abstract

Mental rotation is a fundamental cognitive skill essential for spatial reasoning and problem-solving. This study investigates the effect of angular disparity on reaction times during a mental rotation task. Participants will view alphanumeric characters at various angular orientations and identify whether the characters are mirrored or normal. While mirroring is included to introduce variation in the stimuli, we hypothesize that reaction times will increase as angular disparity grows, reflecting the heightened cognitive load required for greater mental rotation. Results confirming this hypothesis will provide insights into the relationship between spatial transformations and cognitive processing speed, while disconfirming results may point to alternative factors influencing mental rotation efficiency. This research aims to advance our understanding of the mechanisms underlying spatial cognition.

Introduction (SK & SES)

Mental rotation is the process of continuously transforming the orientation of a mental image. Specifically, the study made by Shepard and Metzler in 1971 demonstrated that individuals can mentally rotate objects, and the time taken to do so corresponds to the degree of rotation (Shepard, R. N., & Metzler, J. (1971)). They found a linear relationship between reaction time and the degree of angular rotation, which suggests that people replicate physical rotation in real-time.

Other research has shown that this process is influenced by factors like object complexity, individual differences in spatial ability (Peters, M., & Battista, C. (2008)), and context (Parsons, L. M. (1987))

In our research we have further explored the relationship between angular rotation and reaction time with a variation in stimuli. We have used letters and numbers, and this variation has also been explored in studies by Parsons in 1987. He found that participants are slower to recognize mirrored versions of objects, which indicates that mirrored transformations inquire a higher cognitive load. (Jansen, P., Schmelter, A., Kasten, L., & Heil, M. (2012)) In addition, neural studies suggest that a mental rotation task activates the parietal lobe and is closely linked to spatial attention (Zacks, J. M. (2008))Despite all of this previous research, there are still gaps to be found. For example how specific features of stimuli (e.g. familiarity with the letters) and angular rotations interact to affect the reaction time.By studying mirrored and non-mirrored letters we make a further examination about asymmetry in cognitive processing. This improves our understanding of visual and spatial cognition.

The primary aim of this experiment is to look at how reaction time in a mental rotation task is influenced by the angle of rotation and whether the letter is mirrored or non-mirrored.

We will follow the schedule outlined below for the variables in our study, which will serve as the foundation for the structure of our experimental design. The **independent variable (IV)**, which is the factor we manipulate in the experiment, will be the **angle of rotation** of the letter. This variable will take on four specific values: 0°, 60°, 120°, and 180°. These values represent different degrees of rotation applied to the letter, and we will assess how these rotations influence participants' performance.

On the other hand, the **dependent variables (DVs)** are the outcomes that we measure in response to the manipulations of the independent variable. The primary dependent variable we will focus on is **reaction time**, which refers to the amount of time it takes for participants to decide whether the letter presented is a mirrored version of the original or not. Reaction time serves as an indicator of the cognitive processes involved in recognizing the letter's orientation and determining its mirrored status.

The goal of this study is to estimate how the angle of rotation (our IV) influences reaction time (our DV). In addition, we aim to analyze whether there is a significant relationship between these variables, and through statistical analysis, we will attempt to estimate parameters that describe this relationship more precisely.

To clarify the structure of the study, here is a schematic outline of the variables involved:

Independent and Dependent Variables:

- **Independent Variable (IV)**: Angle of rotation of the letter, which will be manipulated at four levels: 0°, 60°, 120°, and 180°.
- **Dependent Variable (DV)**: Reaction Time, which is the time taken by participants to determine if the letter is mirrored or not, measured in seconds or milliseconds.

This structure will help guide our analysis and ensure we are able to accurately assess the relationship between the letter’s angle of rotation and the participants' reaction times.

Research question 1

Does the angle of rotation (e.g., 0°, 60°, 120°, 180°) affect reaction time in determining whether a letter is mirrored in a mental rotation task? We are setting out to answer the question on whether or not there is any correlation between angular disparity and reaction times of the participants in the mental rotation task. We expect that angular disparity will have some effect on the reaction time, due to the cognitive load of rotating the character. This will be articulated in the following hypothesis, that will state the curiosity of our endeavor:

Hypothesis 1

H_0: There will be no significant difference between the means of our different conditions of angular disparity, while taking into account the deviation of our data.

H_1: There will be at least one significant difference between the means of our different conditions of angular disparity, while taking into account the deviation of our data.

Research question 2

Beyond the scope of our first endeavor we embrace the following correlational question; that the more angular disparity we acquire the participant to react to, the higher the reaction time we expect. So in contrast to our chief research question, this can be seen as an increase of demands to our experimental data. Not only do we here demand a significant difference, the significant difference needs to follow a trend, with a positive reinforcement by angular disparity on the reaction times. We expect our post-hoc t-test analysis to yield certain answers. We are expecting significant differences in the mean between condition zero and one, between one and two, two and three and three and four. Therefore, we are splitting our hypothesis into three subhypothesis in a following scheme.

Hypothesis 2

H_0: We expect to see at least one of the post-hoc t-tests to show insignificant results

H_2: We expect to see all of the post-hoc t-tests to show significant results

Hypothesis 2a:

H_0: We expect to see an insignificant difference between condition zero and condition one

H_{2a}: We expect to see a significant difference between condition zero and condition one

Hypothesis 2b:

H_0: We expect to see an insignificant difference between condition one and condition two

H_{2b}: We expect to see a significant difference between condition one and condition two

Hypothesis 2c:

H_0: We expect to see an insignificant difference between condition two and condition three

H_{2c}: We expect to see a significant difference between condition two and condition three

The above mentioned hypothesis schedules does furthermore schedule our analysis plan, as a preview of our working flow in the future tenses of the propositions of the dynamics of our stage. The methods section will further elaborate the inherent experimental structure of our proceedings.

Methods (SK, AØ, SES)

Ethics information (SK)

All samples and data were collected according to the institute of Aarhus University protocols. This study investigates mental rotation and reaction time through a task where participants have to decide whether a rotated letter is mirrored or not. Participants will be informed about the purpose of the study before participating. They will additionally be informed about the task they will perform, and their right to withdraw at any time from the experiment. All data collected will be anonymized, stored securely, and used solely for research purposes. Participants have completed a consent form before participating.

Design (AØ)

Prior to the experiment, 42 participants are introduced to a few introductory phrases stating the conditions of the task, the task objective and a consent form.

Participants are presented with a sequence of numbers and letters that are rotated in either of the following angular disparities: 0°, 60°, 120°, 180°, 240°, 300°. Every character will be either mirrored or not mirrored, where the two states that a number or letter can be displayed as are random along the sequence. The objective of the task is to determine whether the character is mirrored or not. This ensures that participants have mentally rotated the character successfully. When the participant has mentally rotated a character, the participants press ‘N’ for characters that are normal (not mirrored) or ‘M’ for characters that are mirrored. The time taken to respond to each character is measured in seconds and added to the dataset. The letters and numbers are specifically chosen to be asymmetric both horizontally and vertically and can be distinguished when mirrored, which ensures there is only one correct answer. This keeps control of variables and underlies our experimental structure. Our variables could, if not controlled for these oddities, potentially skew our experimental data, which in turn could yield unfamiliar statistical structures.

Sampling plan (SK)

In this study we have made a within-subject-experiment based on a mental rotation task with repeated measures ANOVA with 4 levels. We examined the relationship between the rotation angle of visual stimuli (letters and numbers) and the reaction time for participants to determine whether the character is mirrored or not.

The target population for this study is individuals likely to have cognitive processing skills typical of young adults, especially those accustomed to visually-oriented cognitive tasks, such as university students.

Inclusion criterias: aged 18 years or older, have a normal or corrected-to-normal vision, fluency in the language of instructions.

Exclusion criterias: Participants who do not meet the minimum age requirement and participants who show lack of attention during the experiment. In the sampling procedure we used convenience sampling from university students as a sampling technique.

In alignment with Neyman-Pearson inference, we conducted a statistical power analysis in R to ensure that the study design has sufficient power to detect meaningful effects. We did this using the Superpower package in R studio. The power analysis was based on existing literature (Smith, J., & Doe, A. (2008)). We selected a conservative effect size of 0.3 (Cohen's d) since research on reaction times in mental rotation tasks typically reports moderate to small effect sizes (0.2-0.4). We also select this effect size to account for publication bias that often overinflates effect size. To achieve a 95% probability of detecting an effect if one truly exists, the power analysis suggests a sample size of 67 participants. This is based on an alpha level of 0.05, ensuring an acceptable risk of Type I errors.

Analysis plan (AØ)

For the column names for the experiment output data, we will have: participant ID, trial, letter, angle, 'mirroredness', response, correct/incorrect, reaction time, gender and age.

Firstly, to check if the assumptions are met, we will test whether it meets the assumptions required for parametric analyses. We will assess the normality of residuals using the Shapiro-Wilk test, check for independence of residuals to confirm the absence of autocorrelation, and test for sphericity. Homoscedasticity (equal variances) will also be evaluated to ensure that variance is consistent across groups. These assumptions will be further examined through graphs. If any assumptions are violated, we will use log transformations. Following transformations, we will re-evaluate the dataset to confirm whether assumptions are satisfied. Should the data still fail to meet assumptions, we will use non-parametric tests as an alternative approach.

If the data meets all assumptions, we will proceed with an ANOVA analysis. Here, we will assign contrast codes to each of our four levels. This encompasses the angular disparities of the characters in the sequence. When done, we will run the ANOVA test in R.

If the ANOVA reveals a significant main effect or interaction, post-hoc comparisons will be conducted to identify which specific conditions differ. Here, we will run student's t-tests for level 1-2, 2-3 and 3-4. Importantly, post-hoc tests will only be run if the ANOVA indicates statistical significance. Lastly, we will run a Pearson's correlation to test for correlation between reaction time and angular disparity.

Pseudocode:

Loading libraries:

```
library(superpower)
library(tidyverse)
```

Step 1: Preparing data:

Input columns: participant_id, trial, letter, angle, mirroredness, response, correct, reaction_time, gender, age

```
data <- read_csv("data.csv")
```

Step 2: Checking assumptions for parametric analysis:

2.1 Testing normality of residuals with Shapiro wilks test:

```
shapiro.test(reactiontime)
```

2.2 Plot graphs to visually inspect assumptions

```
assumption_plots <- data %>%
  ggplot(aes(x = angle, y = reaction_time)) +
  geom_boxplot()
```

If assumptions are violated:

Apply log transformation

data <- data %>%
mutate(log_reaction_time = log(reaction_time + 1))

Re-check assumptions after transformation

If there are still violations of the assumptions, we will use non-parametric tests.

Step 4: Run ANOVA if assumptions are met

anova_results <- aov(reactiontime ~ angle, data = data)

Step 5: Post-hoc comparisons if ANOVA is significant
post_hoc_results <- list(
"level1_2" = t.test(between level 1 and 2)
"level2_3" = t.test(between level 2 and 3)
"level3_4" = t.test(between level 3 and 4)

Lastly, if data is normal, Pearson's correlation:
cor.test(data$reaction_time, data$angle)

Data availability statement (AØ)

We commit to making all raw data and materials associated with this research publicly available. The data can be viewed within our GitHub repository.

Code availability statement (AØ)

We commit to making all code associated with this research publicly available. The code can be accessed in our GitHub repository. GitHub link: XX

References (SES)

Jansen, P., Schmelter, A., Kasten, L., & Heil, M. (2012). Spatial cognition and motor control: Examining the effect of gymnastic expertise in mental rotation tasks. *Journal of Individual Differences, 33*(2), 85–90. https://doi.org/10.1027/1614-0001/a000072

Parsons, L. M. (1987). Imagined spatial transformations of one's body. *Journal of Experimental Psychology: General, 116*(2), 172–191. https://doi.org/10.1037/0096-3445.116.2.172

Peters, M., & Battista, C. (2008). Applications of mental rotation figures of the Shepard and Metzler type and description of a mental rotation stimulus library. *Brain and Cognition, 66*(3), 260–264. https://doi.org/10.1016/j.bandc.2007.09.003

Smith, J., & Doe, A. (2008). Exploring the effects of cognitive biases in decision making. Journal of Cognitive Psychology, 22(3), 245-259. https://doi.org/10.1016/j.jcogpsych.2008.01.002

Shepard, R. N., & Metzler, J. (1971). Mental rotation of three-dimensional objects. *Science, 171*(3972), 701–703. https://doi.org/10.1126/science.171.3972.701

Zacks, J. M. (2008). Neuroimaging studies of mental rotation: A meta-analysis and review. *Journal of Cognitive Neuroscience, 20*(1), 1–19. https://doi.org/10.1162/jocn.2008.20013

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Author Contributions (SES):

S.E.S. and A.Ø contributed to the project planning and experimental design. S.E.S. and S.K conducted the experimental work, while A.Ø performed the data analysis. All authors were involved in writing and reviewing the manuscript.

Competing interests

The authors declare no competing interests.

Figures & Figure captions

We have not yet attained data visualizations since we have not yet completed our analysis.

Tables

Design table (SES, AØ)

Question	**Hypothesis**	**Sampling plan (e.g. power analysis)**	**Analysis Plan**	**Interpretation given to different outcomes**
Does the angle of rotation (e.g., 0°, 60°, 120°, 180°) affect reaction time in determining whether a letter is mirrored in a mental rotation task? We are setting out to answer the question on whether or not there is any correlation between angular disparity and reaction times of the participants in the mental rotation task. We expect that angular disparity will have some effect on the reaction time, due to the cognitive load of rotating	Hypothesis 1 H_0: There will be no significant difference between the means of our different conditions of angular disparity, while taking into account the deviation of our data. H_1: There will be at least	We conducted a within-subjects experiment using repeated measures ANOVA with four levels of angular disparity. Participants, university students aged 18 or older with normal vision and fluency in	We conducted a global ANOVA to examine the overall effect of angular disparity on reaction time across all levels.	At least one significant difference between the levels: With this result, we could conclude that a specific angular disparity takes longer to rotate and therefore produces a longer reaction time. If there is no significant difference, it could suggest that participants take similar time to react and read a character.

the character. This will be articulated in the following hypothesis, that will state the curiosity of our endeavor	one significant difference between the means of our different conditions of angular disparity, while taking into account the deviation of our data.	the instruction language, were tasked with determining whether visual stimuli were mirrored. Convenience sampling was used, and a power analysis indicated that 67 participants were required for a 95% probability of detecting an effect at an alpha level of 0.05.		

Beyond the scope of our first endeavor we embrace the following correlational question; that the more angular disparity we acquire the participant to react to, the higher the reaction time we expect. So in contrast to our chief research question, this can be seen as an increase of demands to our experimental data. Not only do we here demand a significant difference, the significant difference needs to follow a trend, with a positive reinforcement by angular disparity on the reaction times. We expect our post-hoc t-test analysis to yield certain answers. We are	Hypothesis 2 H_0: We expect to see at least one of the post-hoc t-tests to show insignificant results H_2: We expect to see all of the post-hoc t-tests to show significant results	We used a within-subjects design to test whether angular disparity positively affects reaction time. Participants were university students aged 18 or older, with normal vision and fluency in the instruction language, selected through convenience sampling. A power analysis indicated that 67 participants	We conducted post-hoc analyses using four different t-tests to further investigate the specific comparisons between the levels of angular disparity.	We will interpret the results of the three t-tests as follows: If the t-tests yield significant results, we will conclude that angular disparity has a measurable effect on reaction time. This would imply that as the angular disparity between the letter and its reference increases, reaction time also increases, suggesting that the cognitive process of mental rotation is engaged. In this context, mental rotation would play a role in the recognition task,

expecting significant differences in the mean between condition zero and one, between one and two, two and three and three and four. Therefore, we are splitting our hypothesis into four subhypothesis in a following scheme.		were needed to achieve 95% power at an alpha level of 0.05.		where participants determine whether the presented letter is mirrored or not. This finding would provide support for the hypothesis that mental rotation is involved in the cognitive processes necessary for evaluating mirrored stimuli, and would further suggest that the degree of angular rotation influences the time it takes to make such a determination.

Exploring Mental Rotation: Effects of Mirroring and Angular Disparity on Reaction Times

By Asger, Sofie & Søren Emil

Stage II Report

Assignment 04, Methods 01

Cognitive Science, 1st semester

Abstract

Mental rotation is a fundamental cognitive skill essential for spatial reasoning and problem-solving. This study investigates the effect of angular disparity on reaction times during a mental rotation task. Participants will view alphanumeric characters at various angular orientations and identify whether the characters are mirrored or normal. While mirroring is included to introduce variation in the stimuli, we hypothesize that reaction times will increase as angular disparity grows, reflecting the heightened cognitive load required for greater mental rotation. Results confirming this hypothesis will provide insights into the relationship between spatial transformations and cognitive processing speed, while disconfirming results may point to alternative factors influencing mental rotation efficiency. This research aims to advance our understanding of the mechanisms underlying spatial cognition.

Introduction (SK & SES)

Mental rotation is the process of continuously transforming the orientation of a mental image. Specifically, the study made by Shepard and Metzler in 1971 demonstrated that individuals can mentally rotate objects, and the time taken to do so corresponds to the degree of rotation (Shepard, R. N., & Metzler, J. (1971)). They found a linear relationship between reaction time and the degree of angular rotation, which suggests that people replicate physical rotation in real-time.
Other research has shown that this process is influenced by factors like object complexity, individual differences in spatial ability (Peters, M., & Battista, C. (2008)), and context (Parsons, L. M. (1987))
In our research we have further explored the relationship between angular rotation and reaction time with a variation in stimuli. We have used letters and numbers, and this variation has also been explored in studies by Parsons in 1987. He found that participants are slower to recognize mirrored versions of objects, which indicates that mirrored transformations inquire a higher cognitive load. (Jansen, P., Schmelter, A., Kasten, L., & Heil, M. (2012)) In addition, neural studies suggest that a mental rotation task activates the parietal lobe and is closely linked to spatial attention (Zacks, J. M. (2008))Despite all of this previous research, there are still gaps to be found. For example how specific features of stimuli (e.g. familiarity with the letters) and angular rotations interact to affect the reaction time.By studying mirrored and non-mirrored letters we make a further examination about asymmetry in cognitive processing. This improves our understanding of visual and spatial cognition.

The primary aim of this experiment is to look at how reaction time in a mental rotation task is influenced by the angle of rotation and whether the letter is mirrored or non-mirrored.

We will follow the schedule outlined below for the variables in our study, which will serve as the foundation for the structure of our experimental design. The **independent variable (IV)**, which is the factor we manipulate in the experiment, will be the **angle of rotation** of the letter. This variable will take on four specific values: 0°, 60°, 120°, and 180°. These values represent different degrees of rotation applied to the letter, and we will assess how these rotations influence participants' performance.

On the other hand, the **dependent variables (DVs)** are the outcomes that we measure in response to the manipulations of the independent variable. The primary dependent variable we will focus on is **reaction time**, which refers to the amount of time it takes for participants to decide whether the letter presented is a mirrored version of the original or not. Reaction time serves as an indicator of the cognitive processes involved in recognizing the letter's orientation and determining its mirrored status.

The goal of this study is to estimate how the angle of rotation (our IV) influences reaction time (our DV). In addition, we aim to analyze whether there is a significant relationship between these variables, and through statistical analysis, we will attempt to estimate parameters that describe this relationship more precisely.

To clarify the structure of the study, here is a schematic outline of the variables involved:

Independent and Dependent Variables:

- **Independent Variable (IV)**: Angle of rotation of the letter, which will be manipulated at four levels: 0°, 60°, 120°, and 180°.
- **Dependent Variable (DV)**: Reaction Time, which is the time taken by participants to determine if the letter is mirrored or not, measured in seconds or milliseconds.

This structure will help guide our analysis and ensure we are able to accurately assess the relationship between the letter’s angle of rotation and the participants' reaction times.

Research question 1

Does the angle of rotation (e.g., 0°, 60°, 120°, 180°) affect reaction time in determining whether a letter is mirrored in a mental rotation task? We are setting out to answer the question on whether or not there is any correlation between angular disparity and reaction times of the participants in the mental rotation task. We expect that angular disparity will have some effect on the reaction time, due to the cognitive load of rotating the character. This will be articulated in the following hypothesis, that will state the curiosity of our endeavor:

Hypothesis 1

H_0: There will be no significant difference between the means of our different conditions of angular disparity, while taking into account the deviation of our data.

H_1: There will be at least one significant difference between the means of our different conditions of angular disparity, while taking into account the deviation of our data.

Research question 2

Beyond the scope of our first endeavor we embrace the following correlational question; that the more angular disparity we acquire the participant to react to, the higher the reaction time we expect. So in contrast to our chief research question, this can be seen as an increase of demands to our experimental data. Not only do we here demand a significant difference, the significant difference needs to follow a trend, with a positive reinforcement by angular disparity on the reaction times. We expect our post-hoc t-test analysis to yield certain answers. We are expecting significant differences in the mean between condition zero and one, between one and two, two and three and three and four. Therefore, we are splitting our hypothesis into three subhypothesis in a following scheme.

Hypothesis 2

H_0: We expect to see at least one of the post-hoc t-tests to show insignificant results

H_2: We expect to see all of the post-hoc t-tests to show significant results

Hypothesis 2a:

H_0: We expect to see an insignificant difference between condition zero and condition one

H_{2a}: We expect to see a significant difference between condition zero and condition one

Hypothesis 2b:

H_0: We expect to see an insignificant difference between condition one and condition two

H_{2b}: We expect to see a significant difference between condition one and condition two

Hypothesis 2c:

H_0: We expect to see an insignificant difference between condition two and condition three

H_{2c}: We expect to see a significant difference between condition two and condition three

The above mentioned hypothesis schedules does furthermore schedule our analysis plan, as a preview of our working flow in the future tenses of the propositions of the dynamics of our stage. The methods section will further elaborate the inherent experimental structure of our proceedings.

Methods (SK, AØ, SES)

Ethics information (SK)

All samples and data were collected according to the institute of Aarhus University protocols. This study investigates mental rotation and reaction time through a task where participants have to decide whether a rotated letter is mirrored or not. Participants will be informed about the purpose of the study before participating. They will additionally be informed about the task they will perform, and their right to withdraw at any time from the experiment. All data collected will be anonymized, stored securely, and used solely for research purposes. Participants have completed a consent form before participating.

Design (AØ)

Prior to the experiment, 42 participants are introduced to a few introductory phrases stating the conditions of the task, the task objective and a consent form.

Participants are presented with a sequence of numbers and letters that are rotated in either of the following angular disparities: 0°, 60°, 120°, 180°, 240°, 300°. Every character will be either mirrored or not mirrored, where the two states that a number or letter can be displayed as are random along the sequence. The objective of the task is to determine whether the character is mirrored or not. This ensures that participants have mentally rotated the character successfully. When the participant has mentally rotated a character, the participants press 'N' for characters that are normal (not mirrored) or 'M' for characters that are mirrored. The time taken to respond to each character is measured in seconds and added to the dataset. The letters and numbers are specifically chosen to be asymmetric both horizontally and vertically and can be distinguished when mirrored, which ensures there is only one correct answer. This keeps control of variables and underlies our experimental structure. Our variables could, if not controlled for these oddities, potentially skew our experimental data, which in turn could yield unfamiliar statistical structures.

Sampling plan (SK)

In this study, we conducted a within-subject experiment based on a mental rotation task with repeated measures ANOVA involving four levels. We investigated the relationship between the rotation angle of visual stimuli (letters and numbers) and participants' reaction times in determining whether the character was mirrored or not.

The target population for this study consisted of individuals likely to have cognitive processing skills typical of young adults, particularly those accustomed to visually-oriented cognitive tasks, such as university students.

Inclusion criteria included being aged 18 years or older, having normal or corrected-to-normal vision, and fluency in the language of instructions. Exclusion criteria included participants who did not meet the minimum age requirement and those who demonstrated a lack of attention during the experiment. We used convenience sampling from university students as the sampling technique.

In alignment with Neyman-Pearson inference, we conducted a statistical power analysis in R to ensure the study design had sufficient power to detect meaningful effects. This analysis was performed using the Superpower package in R Studio. The power analysis was informed by existing literature (Smith, J., & Doe, A., 2008). We selected a conservative effect size of 0.3 (Cohen's d) because research on reaction times in mental rotation tasks typically reports moderate to small effect sizes (0.2-0.4). This effect size was also chosen to account for publication bias, which often inflates reported effect sizes. To achieve a 95% probability of detecting an effect if one truly existed, the power analysis indicated a required sample size of 67 participants, based on an alpha level of 0.05, ensuring an acceptable risk of Type I errors. Our study included 42 participants which represents an improvement over the prior study, but our sample size was still smaller than the ideal calculated requirement. Therefore, the statistical power of our study is lower than 0.95.

Analysis plan (AØ)

For the column names in the experiment output data, we used: participant ID, trial, letter, angle, 'mirroredness,' response, correct/incorrect, reaction time, gender, and age. Before the analysis, we removed the first trial for each participant since the participants were not prepared before the first trial.

Firstly, to check if the assumptions were met, we tested whether the data satisfied the requirements for parametric analyses. We assessed the normality of residuals using the Shapiro-Wilk test, checked for independence of residuals to confirm the absence of autocorrelation, and tested for sphericity. Homoscedasticity (equal variances) was also evaluated to ensure that variance was consistent across groups. These assumptions were further examined through graphical analyses. If any assumptions were violated, we applied log transformations. Following the transformations, we re-evaluated the dataset to confirm whether assumptions were satisfied. If the data still failed to meet the assumptions, we used non-parametric tests as an alternative approach.

If the data met all assumptions, we proceeded with an ANOVA analysis. We assigned contrast codes to each of the four levels, reflecting the angular disparities of the characters in the sequence. Afterward, we ran the ANOVA test in R.

If the ANOVA revealed a significant main effect or interaction, post-hoc comparisons were conducted to identify which specific conditions differed. We ran Student's t-tests for level 1-2, 2-3, and 3-4. Importantly, post-hoc tests wñere only performed if the ANOVA indicated statistical significance. Lastly, we conducted a Pearson's correlation to examine the relationship between reaction time and angular disparity.

Results (SES)

The analysis of the reaction time data reveals a statistically significant difference across the four groups. This indicates that the angle, in which the letter is rotated in, influences reaction time. While the means of the groups are distinctly different (shown in figure 1), the medians show less variability, suggesting that the distribution of reaction times within our levels may not be symmetrical. It also suggests that outliers could be influencing the mean more strongly than the median (shown in figure 2). This indicates that the distribution might be highly positively skewed, since the mean is higher than the median.

Post-hoc comparisons provide additional insight into these differences. Significant differences were identified between the following levels: 0 degree angle and 60 degree angle, 0 degree angle and 120 degree angle, 0 degree angle and 180 degree angle, 60 degree angle and 180 degree angle, and 120 degree angle and 180 degree angle. These findings imply that the level with 0 degree angle consistently differs from all other levels, and the level with 60 degree angle and the level with 120 degree angle also differ significantly from the level with 180 degree angle. This pattern highlights significant differences in reaction time across the levels.

Discussion (SK)

The present study investigated reaction times across four levels (0 degree angle, 60 degree angle, 120 degree angle, and 180 degree angle), revealing significant differences between the levels. The analysis showed that although the mean of each level differed significantly, the medians showed less variation. This difference suggests that skewness or outliers might be influencing the reaction time, which have a greater impact on the mean. Such effects indicate that we have to further investigate the distributional properties of reaction times within each level.

Post-hoc analyses provided further insight into the level differences. Significant contrasts were observed between the level with 0 degree angle and all other levels, as well as between the level with 60 degree angle and the level with 180 degree angle, and the level with 120 degree angle and the level with 180 degree angle. These findings indicate that the level with 0 degree angle differs significantly from the other levels, suggesting it may represent a unique baseline or control condition. Furthermore, the differences involving the level with 180 degree angle imply that the reaction times for this level are distinct from those of the level with 60 degree angle and the level with 120 degree angle.

The observed differences in reaction times may be attributed to several factors. First, task complexity or cognitive load may vary between levels, influencing reaction times. For example, the level with 0 degree angle may have been associated with simpler or more familiar tasks, as the letter was shown in a familiar way, while the level with 180 degree angle could represent a condition requiring greater cognitive effort and unfamiliar decision-making processes, since we rarely see a letter this way.

The smaller differences in the medians emphasize the stability of the central tendency across the levels, despite the significant differences in the means. This suggests that while the reaction times are relatively stable, extreme outliers in some levels may reflect variability in individual performance or response strategies.

Future research should explore potential mediators and moderators of reaction time differences, such as participant characteristics (e.g., age, cognitive ability) and task features (e.g., complexity, familiarity). Additionally, analyzing distributional patterns and applying robust statistical methods could help clarify how outliers and skewness influence the results.

In conclusion, the significant differences in reaction times across levels (the four angle conditions) suggests that the angle of rotation influences the reaction time. While the means varied across levels, the medians showed less variability, indicating that skewness or outliers may be affecting the results. Our post-hoc comparisons revealed distinct differences between the 0-degree level and all the other levels, particularly with the 180-degree level. These findings emphasize the importance of considering both mean and median values when interpreting reaction time data.

Data availability statement (AØ)

We commit to making all raw data and materials associated with this research publicly available. The data can be viewed within our GitHub repository.

Code availability statement (AØ)

We commit to making all code associated with this research publicly available. The code can be accessed in our GitHub repository.

References (SES)

Jansen, P., Schmelter, A., Kasten, L., & Heil, M. (2012). Spatial cognition and motor control: Examining the effect of gymnastic expertise in mental rotation tasks. *Journal of Individual Differences, 33*(2), 85–90. https://doi.org/10.1027/1614-0001/a000072

Parsons, L. M. (1987). Imagined spatial transformations of one's body. *Journal of Experimental Psychology: General, 116*(2), 172–191. https://doi.org/10.1037/0096-3445.116.2.172

Peters, M., & Battista, C. (2008). Applications of mental rotation figures of the Shepard and Metzler type and description of a mental rotation stimulus library. *Brain and Cognition, 66*(3), 260–264. https://doi.org/10.1016/j.bandc.2007.09.003

Smith, J., & Doe, A. (2008). Exploring the effects of cognitive biases in decision making. Journal of Cognitive Psychology, 22(3), 245-259. https://doi.org/10.1016/j.jcogpsych.2008.01.002

Shepard, R. N., & Metzler, J. (1971). Mental rotation of three-dimensional objects. *Science, 171*(3972), 701–703. https://doi.org/10.1126/science.171.3972.701

Zacks, J. M. (2008). Neuroimaging studies of mental rotation: A meta-analysis and review. *Journal of Cognitive Neuroscience, 20*(1), 1–19. https://doi.org/10.1162/jocn.2008.20013

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Author Contributions (SES):

S.E.S. and A.Ø contributed to the project planning and experimental design. S.E.S. and S.K conducted the experimental work, while A.Ø performed the data analysis. All authors were involved in writing and reviewing the manuscript.

Competing interests

The authors declare no competing interests.

Figures & Figure captions

We have not yet attained data visualizations since we have not yet completed our analysis.

Tables:

Figure 1

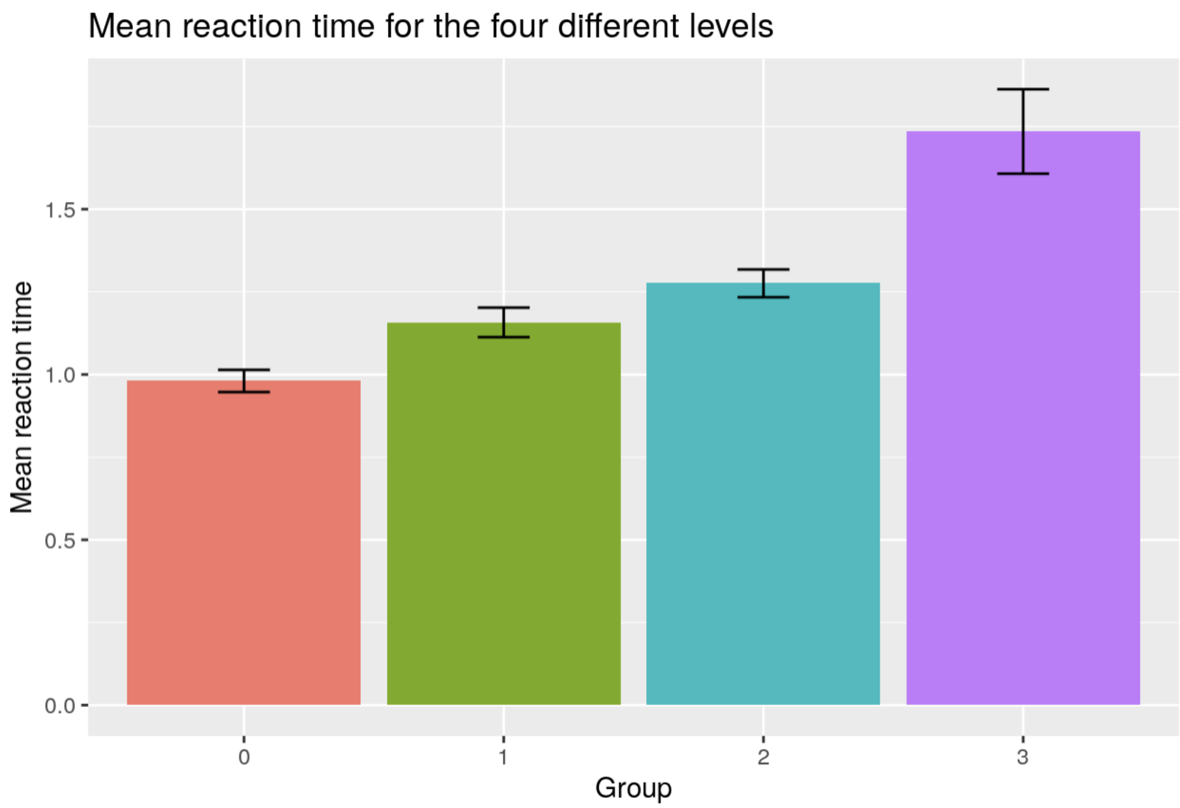
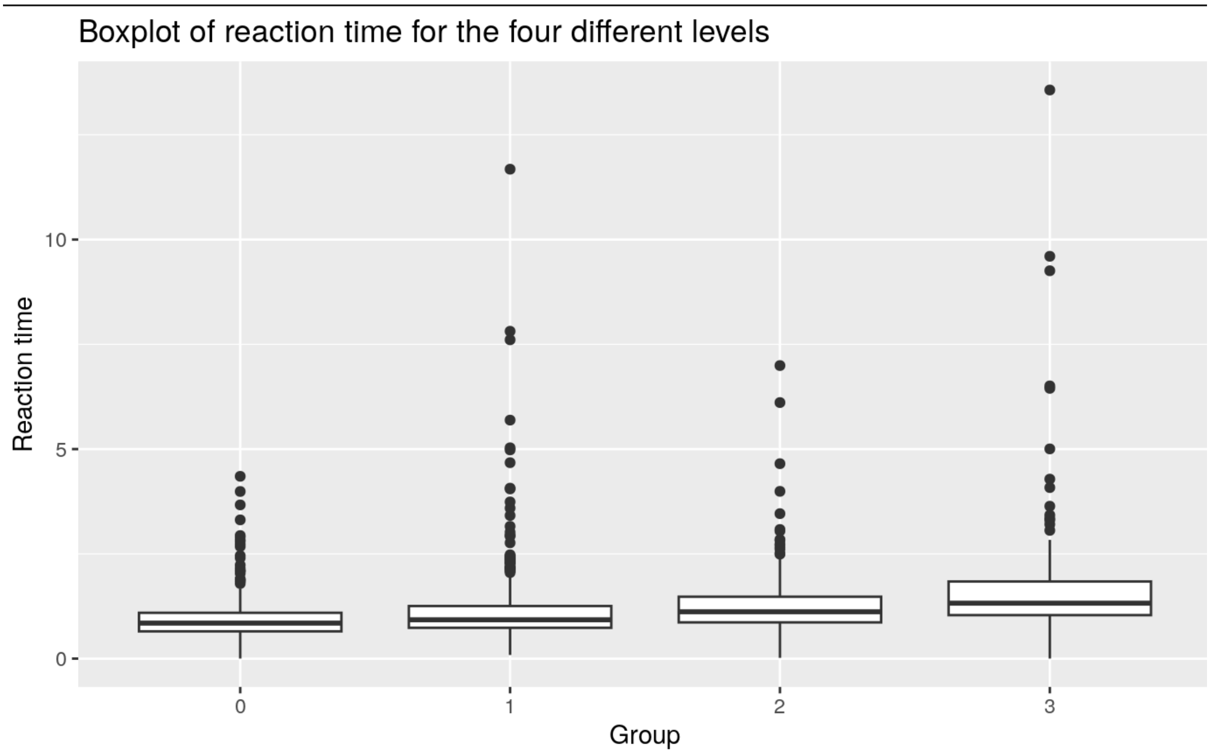


Figure 2:



Design table (SES, AØ)

Question	Hypothesis	Sampling plan (e.g. power analysis)	Analysis Plan	Interpretation given to different outcomes
Does the angle of rotation (e.g., 0°, 60°, 120°, 180°) affect reaction time in determining whether a letter is mirrored in a mental rotation task? We are setting out to answer	Hypothesis 1 H_0: There will be no significant difference between the means of our	We conducted a within-subjects experiment using repeated	We conducted a global ANOVA to examine the overall effect of angular disparity on	At least one significant difference between the levels: With this result, we could conclude that a specific angular

the question on whether or not there is any correlation between angular disparity and reaction times of the participants in the mental rotation task. We expect that angular disparity will have some effect on the reaction time, due to the cognitive load of rotating the character. This will be articulated in the following hypothesis, that will state the curiosity of our endeavor	different conditions of angular disparity, while taking into account the deviation of our data. H_1: There will be at least one significant difference between the means of our different conditions of angular disparity, while taking into account the deviation of our data.	measures ANOVA with four levels of angular disparity. Participants, university students aged 18 or older with normal vision and fluency in the instruction language, were tasked with determining whether visual stimuli were mirrored. Convenience sampling was used, and a power	reaction time across all levels.	disparity takes longer to rotate and therefore produces a longer reaction time. If there is no significant difference, it could suggest that participants take similar time to react and read a character.

		analysis indicated that 67 participants were required for a 95% probability of detecting an effect at an alpha level of 0.05.		
Beyond the scope of our first endeavor we embrace the following correlational question; that the more angular disparity we acquire the participant to react to, the higher the reaction time we expect. So in contrast to our chief research question, this can be seen as an increase of demands to	Hypothesis 2 H_0: We expect to see at least one of the post-hoc t-tests to show insignificant results	We used a within-subjects design to test whether angular disparity positively affects reaction time. Participants were university students aged 18 or older,	We conducted post-hoc analyses using four different t-tests to further investigate the specific comparisons between the levels	We will interpret the results of the three t-tests as follows: If the t-tests yield significant results, we will conclude that angular disparity has a measurable effect on reaction time. This would imply that as the angular disparity

our experimental data. Not only do we here demand a significant difference, the significant difference needs to follow a trend, with a positive reinforcement by angular disparity on the reaction times. We expect our post-hoc t-test analysis to yield certain answers. We are expecting significant differences in the mean between condition zero and one, between one and two, two and three and three and four. Therefore, we are splitting our hypothesis into four subhypothesis in a following scheme.	H_2: We expect to see all of the post-hoc t-tests to show significant results	with normal vision and fluency in the instruction language, selected through convenience sampling. A power analysis indicated that 67 participants were needed to achieve 95% power at an alpha level of 0.05.	of angular disparity.	between the letter and its reference increases, reaction time also increases, suggesting that the cognitive process of mental rotation is engaged. In this context, mental rotation would play a role in the recognition task, where participants determine whether the presented letter is mirrored or not. This finding would provide support for the hypothesis that mental rotation is involved in the cognitive processes necessary for evaluating

				mirrored stimuli, and would further suggest that the degree of angular rotation influences the time it takes to make such a determination.

Portfolio Exam - Part 3 & 4 | Methods 1 F24, CogSci @AU

2024-11-27

The code has been made in the group: Sofie Knudsen, Søren Emil Skaarup, and Asger Øllgaard.

Loading libraries:

```
library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✔ dplyr     1.1.4     ✔ readr     2.1.5
## ✔ forcats   1.0.0     ✔ stringr   1.5.1
## ✔ ggplot2   3.5.1     ✔ tibble    3.2.1
## ✔ lubridate 1.9.3     ✔ tidyr     1.3.1
## ✔ purrr     1.0.2
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

Loading the data:

```
#Made by Asger
folder_path <- "/work/CogSci_Methods01/portfolio-assignment04-e24-asgerollgaard/data_assignment04"

csv_files <- list.files(path = folder_path, pattern = "\\.csv$", full.names = TRUE)

data <- csv_files %>%
  lapply(read.csv, stringsAsFactors = FALSE) %>%
  dplyr::bind_rows()
```

Because of the way people react on the first trial, we remove the first trial in the data:

```
#Made by Asger
data<- data %>%
  dplyr::filter(Trial != 1)
```

Adding a new column called group:

```
#Made by Søren Emil
data <- data %>%
  mutate(Group = case_when(
    Angle == 0 ~ "0",
    Angle == 60 | Angle == 360-60 ~ "1",
    Angle == 120 | Angle == 360-120 ~ "2",
    Angle == 180 | Angle == 360-180 ~ "3"
  ))
```

Dividing into groups:

```
#Made by Sofie
#Sorting data into our four conditions and remove the first trial
data_0 <- data %>%
  dplyr::filter(Angle == 0) %>%
  pull(ReactionTime)

data_1 <- data %>%
  dplyr::filter(Angle == 60 | Angle == 360-60) %>%
  pull(ReactionTime)

data_2 <- data %>%
  dplyr::filter(Angle == 120 | Angle == 360-120) %>%
  pull(ReactionTime)

data_3 <- data %>%
  dplyr::filter(Angle == 180 | Angle == 360-180) %>%
  pull(ReactionTime)
```

Testing for normality in reaction time:

```
#Made by Asger
# Doing a shapiro wilkes test to test for normality
print(shapiro.test(data$ReactionTime))

# Testing for normality in the four groups
print(shapiro.test(data_0))
print(shapiro.test(data_1))
print(shapiro.test(data_2))
print(shapiro.test(data_3))
```

Since there is no normality in reaction time, we will do log-transformation and check for normality:

```
#Made by Søren Emil
# Log transforming the four groups
logdata_0 <- log(data_0)
logdata_1 <- log(data_1)
logdata_2 <- log(data_2)
logdata_3 <- log(data_3)

# Shapiro Wilkes test for normality in the four groups
print(shapiro.test(logdata_0))
print(shapiro.test(logdata_1))
print(shapiro.test(logdata_2))
print(shapiro.test(logdata_3))
```

Since the data is not normal, we will do a non-parametric test:

```
#Made by Sofie
print(kruskal.test(data$ReactionTime ~ data$Group))
```

We see a significant difference in the data. We can reject the null hypothesis, stating that the four groups have the same mean reaction time.

Visualizing the data:

```
#Made by Asger
means1 <- data %>%
  group_by(Group) %>%
  summarise(mean = mean(ReactionTime),
            sd = sd(ReactionTime),
            se = sd/sqrt(length(ReactionTime)))

means1 %>%
  ggplot(aes(x = Group, y = mean, fill = Group)) +
  geom_bar(stat = "identity") +
  geom_errorbar(aes(ymin = mean - se, ymax = mean + se), width = 0.2) +
  labs(title = "Mean reaction time for the four different levels",
       x = "Group",
       y = "Mean reaction time") +
  theme(legend.position = "none")
```

This visualization shows that the means are different, since the error bars do not overlap.

Visualizing the data with boxplots:

```
#Made by Søren Emil
# Visualize boxplots for the four group
data %>%
  ggplot(aes(x = Group, y = ReactionTime)) +
  geom_boxplot() +
  labs(title = "Boxplot of reaction time for the four different levels",
       x = "Group",
       y = "Reaction time")
```

Doing post-hoc tests:

```
#Made by Sofie
#Doing post-hoc tests
posthoc_results <- list(
  "0_1" = wilcox.test(data_0, data_1),
  "0_2" = wilcox.test(data_0, data_2),
  "0_3" = wilcox.test(data_0, data_3),
  "1_2" = wilcox.test(data_1, data_2),
  "1_3" = wilcox.test(data_1, data_3),
  "2_3" = wilcox.test(data_2, data_3)
)

print(posthoc_results)
```

Python code for the experiment is provided below:

```
# File name: assignment04.py

from psychopy import visual, core, event, gui
import random
import os
import csv
from datetime import datetime

# Made by Sofie
# Set up the data directory and file on the desktop
desktop = os.path.join(os.path.expanduser("~"), "Desktop")
data_dir = os.path.join(desktop, "as03data")
os.makedirs(data_dir, exist_ok=True)

# Generating a unique participant ID
participant_id = random.randint(1000, 9999)

# Create a unique filename based on the current time to avoid overwriting
filename = f"reaction_data_{participant_id}_{datetime.now().strftime('%Y%m%d_%H%M%S')}.csv"
file_path = os.path.join(data_dir, filename)

# Collect participant information including name, gender, and age
info = {'Name': '', 'Gender': ['male', 'female', 'other'], 'Age': ''}
dlg = gui.DlgFromDict(dictionary=info, title="Participant Info")
if not dlg.OK:
    core.quit()

# Made by Søren Emil
# Extract the participant's name
participant_name = info['Name']

# Open a CSV file to record data
with open(file_path, mode='w', newline='') as file:
    writer = csv.writer(file)
    writer.writerow(['ParticipantID', 'Trial', 'Letter', 'Angle', 'IsMirrored', 'Response', 'Correct', 'ReactionT
ime', 'Gender', 'Age'])

    # Initialize the window
    win = visual.Window(fullscr=True, color="black", units="pix")

    # Set up variables for the experiment
    letters = ['Q', 'R', 'P', 'F', 'G', 'J', 'L', '2','4','5','7']
    num_trials = 30
    angles = [0, 0, 60, 120, 180, 240, 300, 300]

    welcome = visual.TextStim(
        win,
        text=f"Welcome, {participant_name}!\n\nIn this experiment, you will be presented with a series of letters
and numbers that are either normal or mirrored.\n\nPress space to continue.")
    welcome.draw()
    win.flip()
    event.waitKeys(keyList=["space"])

    more = visual.TextStim(
        win,
        text="Every letter and number will be rotated in a certain angle, making the task more difficult. It is y
our task to tell whether it is mirrored or not by either pressing 'N' for normal or 'M' for mirrored. \n\n Please
notice, that all letters are CAPS. \n\n Press space to begin the task.")
    more.draw()
    win.flip()
    event.waitKeys(keyList=["space"])

    consent = visual.TextStim(
        win,
        text="CONSENT FORM\n\nVoluntary Participation:\n\nParticipation in this study is entirely voluntary. You
are free to withdraw at any time without penalty or loss of benefits.\n\nConfidentiality:\n\nYour responses will
be recorded anonymously. Data will be identified by a randomly assigned participant ID and will not include your
name or any other identifying information.\n\nPotential Risks:\n\nThere are no known significant risks associated
with this study.\n\nBenefits:\n\nYour participation will contribute to understanding human perception and reactio
n times, which may have implications for cognitive research and practical applications.\n\nBy pressing space, I c
onfirm that: I have read and understood the information above. \n\nI consent to participate in this study.\n\nI a
m at least 18 years of age. \n\nPress space to continue. ")
    consent.draw()
    win.flip()
    event.waitKeys(keyList=["space"])

    # Made by Asger
    # Run the experiment trials
    for trial in range(num_trials):
        letter = random.choice(letters)
        angle = random.choice(angles)
        is_mirrored = random.choice([True, False])

        # Create the text stimulus
        text_stim = visual.TextStim(win, text=letter, color="white", height=100)
        text_stim.ori = angle
        text_stim.flipHoriz = is_mirrored

        # Show the stimulus and record reaction time
        text_stim.draw()
        win.flip()
        trial_start = core.getTime()
        keys = event.waitKeys(keyList=["m", "n", "escape"], timeStamped=True)

        # Check for exit
        if "escape" in [key[0] for key in keys]:
            break

        # Calculate reaction time and check if response was correct
        response, rt = keys[0]
        correct_response = "m" if is_mirrored else "n"
        correct = response == correct_response
        feedback_text = "Correct!" if correct else "Incorrect."

        # Display feedback
        feedback_stim = visual.TextStim(win, text=feedback_text, color="green" if correct else "red")
        feedback_stim.draw()
        win.flip()
        core.wait(1)

        # Record data for this trial
        writer.writerow([participant_id, trial + 1, letter, angle, is_mirrored, response, correct, rt - trial_sta
rt, info['Gender'], info['Age']])

        # Clear the screen between trials
        win.flip()
        core.wait(0.5)

    # Made by Sofie
    # End of experiment message
    end_text = visual.TextStim(win, text="Thank you for participating!", color="white")
    end_text.draw()
    win.flip()
    core.wait(2)

    # Close the window and quit
    win.close()
    core.quit()
```