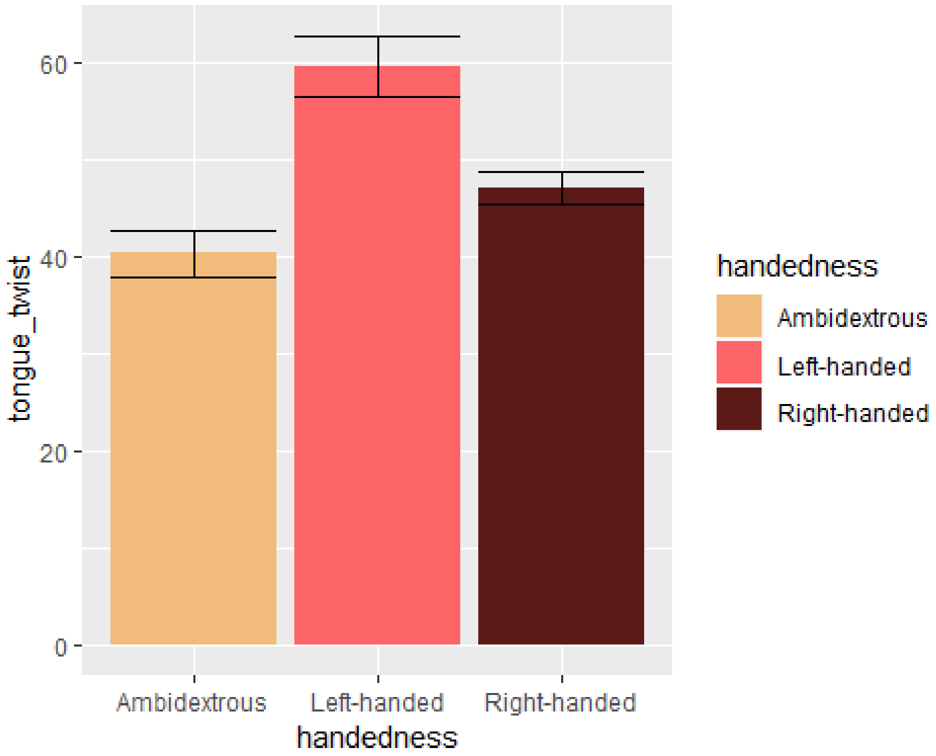
Experimental Methods I - portfolio exam

Peter Andreas Mikkelsen Thramkrongart

Portfolio 1: Datamining of the CogSci 2018 Personality Data

1) Who, on average, is faster at the tongue twister task, right-handers or left-handers?

```
# Grouping by handedness and finding the mean of tongue_twist
byHandedness <- group_by(df, handedness)
summarise(byHandedness, tongue_twist = mean(tongue_twist))

## # A tibble: 3 x 2
##   handedness   tongue_twist
##   <fct>               <dbl>
## 1 Ambidextrous         40.4
## 2 Left-handed          59.7
## 3 Right-handed         47.2

# Making bar graoh with errorbars and colour coding by handedness
ggplot(df, aes(x=handedness, y=tongue_twist,fill=handedness)) +
geom_bar(stat = "summary",fun.y=mean) +
geom_errorbar(stat = "summary", fun.data = mean_se)+scale_fill_manual(value
s=wes_palette("GrandBudapest1"))
```

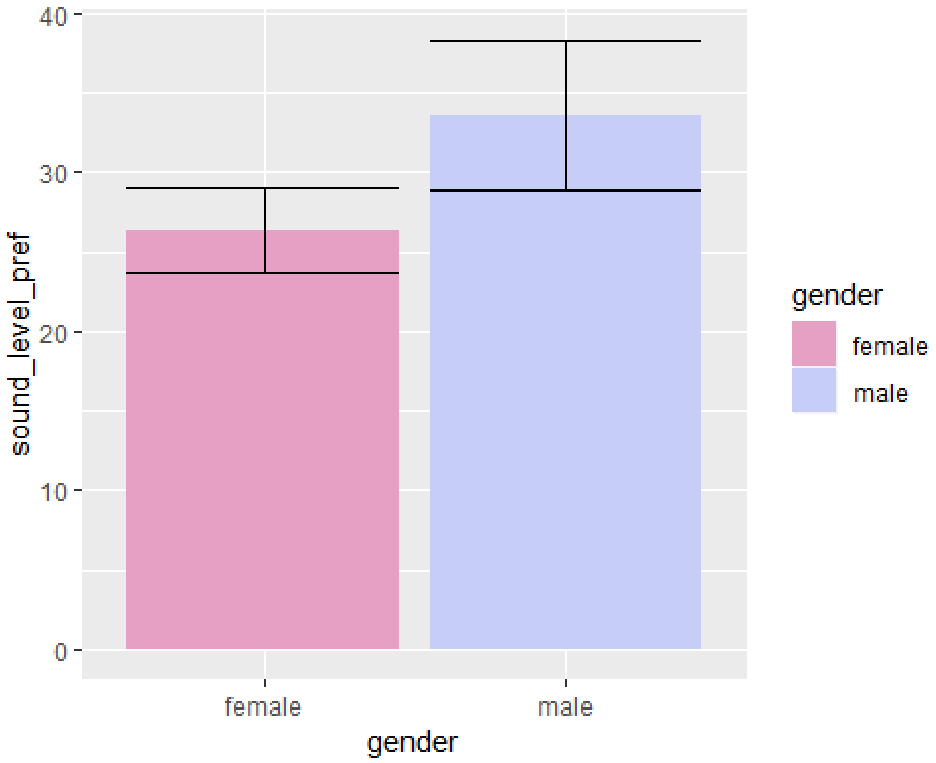


Conclusion:

according to our data left-handed cog-sci'ers are fastest at doing the tongue twister task.

2) Who prefers higher volumes of music, males or females?

```
# Grouping by gender and finding the mean of preferred sound level
byGender <- group_by(df, gender)
summarise(byGender, sound_level_pref = mean(sound_level_pref ))

## # A tibble: 2 x 2
##   gender sound_level_pref
##   <fct>             <dbl>
## 1 female             26.4
## 2 male               33.6

# Making a bar graph with errorbars
ggplot(df, aes(x=gender, y=sound_level_pref,fill=gender))+scale_fill_manual
(values = wes_palette("GrandBudapest2")) +
geom_bar(stat = "summary",fun.y=mean) +
geom_errorbar(stat = "summary", fun.data = mean_se)
```



Conclusion:

Male cog-sci'ers prefer louder music than females.

(33.6>26.4)

3) Is there a relation between occular dominance and the rabbit-duck illusion?

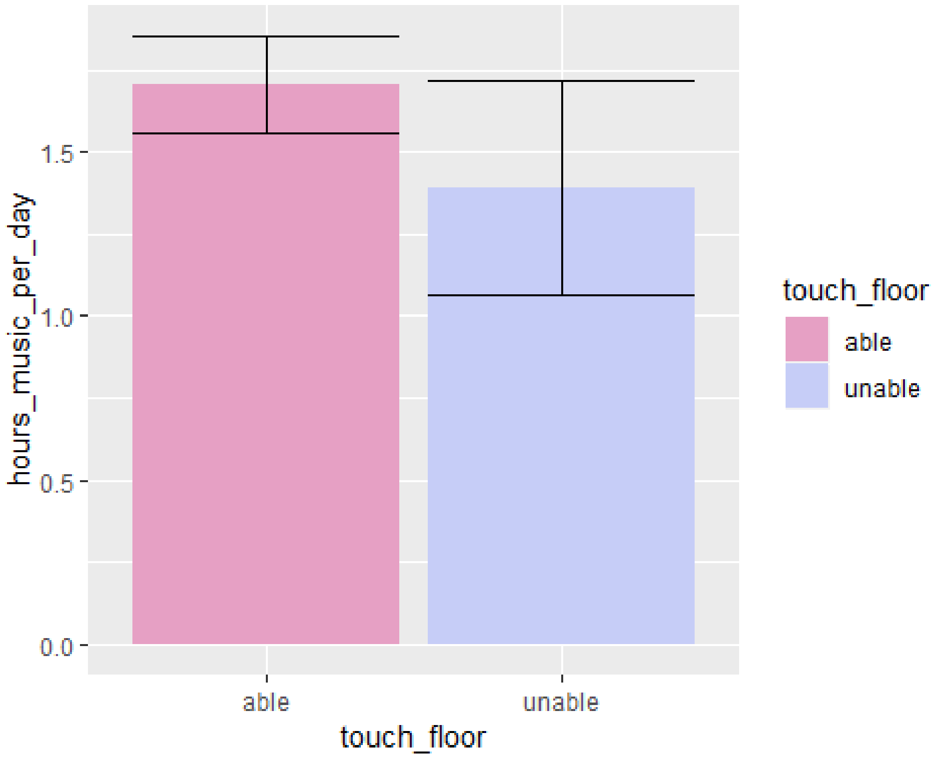
```
#grouping by ocular dominance and summarising
byOcularDom <- group_by(df, ocular_dom,vis_duck) %>% summarise(n())

byOcularDom

## # A tibble: 6 x 3
## # Groups:   ocular_dom [?]
##   ocular_dom vis_duck `n()`
##   <fct>      <fct>    <int>
## 1 Both       Duck         3
## 2 Both       Rabbit       5
## 3 Left       Duck        14
## 4 Left       Rabbit       7
## 5 Right      Duck        19
## 6 Right      Rabbit       9
```

conclusion:

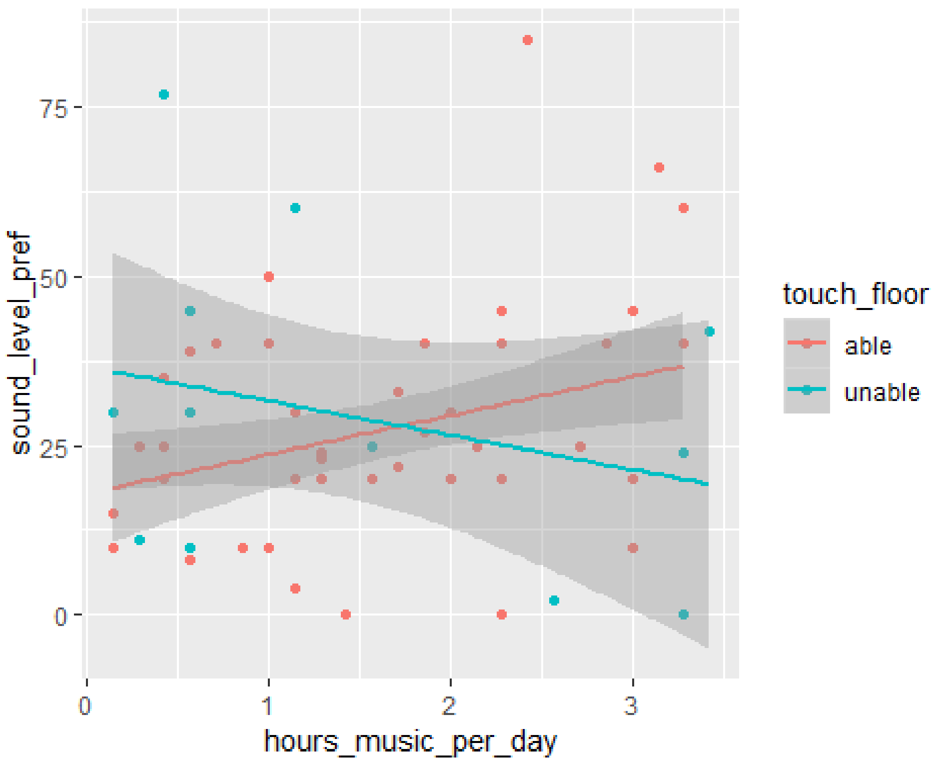
Cog-sci'ers with a dominant eye first see the duck. That distribution is not seen with cog-sci'ers who have no ocular dominance.

4) Calculate the average music consumption per day for those who can touch the floor and those who can't. Do you observe a relation between music consumption and preference for volume in the two groups (just from looking at the data and graph)?

```
# Fixing data
df$touch_floor <-ifelse(df$touch_floor=="Yes"|df$touch_floor=="Yes, of cour
se!!", "able","unable")

df$hours_music_per_week[df$hours_music_per_week=="two"] <- 2
df$hours_music_per_week<- as.numeric(df$hours_music_per_week)
df2<-subset(df,hours_music_per_week<500)
df2$hours_music_per_day<-df2$hours_music_per_week/7

#grouping by ability  touch the floor
byFloorTouchers <- group_by(df2,touch_floor)

dplyr::summarise(byFloorTouchers, hours_music_per_day = mean(hours_music_pe
r_day))

## # A tibble: 2 x 2
##   touch_floor hours_music_per_day
##   <chr>                     <dbl>
## 1 able                       1.70
## 2 unable                     1.39

# Making bar graph
ggplot(df2, aes(x=touch_floor,y=hours_music_per_day,fill=touch_floor))+scal
e_fill_manual(values = wes_palette("GrandBudapest2")) +
geom_bar(stat = "summary",fun.y=mean) +
geom_errorbar(stat = "summary", fun.data = mean_se)
```




```
#making scatterplot
ggplot(df2,aes(x=hours_music_per_day,y=sound_level_pref,color=touch_floor))
+geom_point()+geom_smooth(method=rlm)
```



Conclusion:

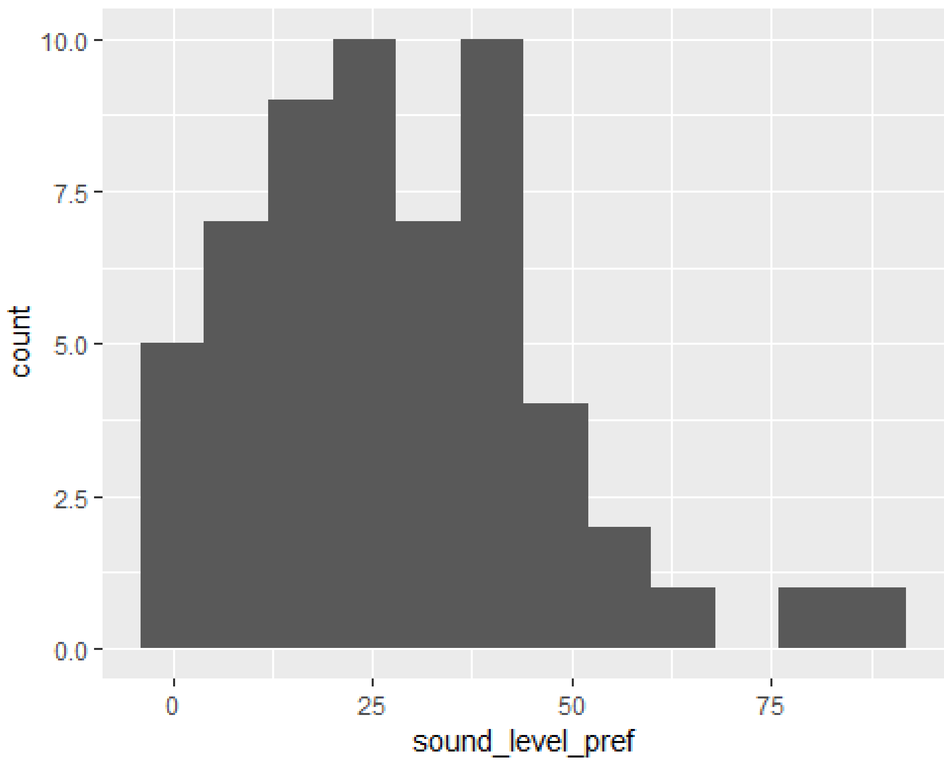
Cog sci'ers able to touch the floor listen to 1.7 hours of music a day on average. Cog sci'ers unable to touch the floor listen to 1.6 hours of music a day on average.

Conclusion 2:

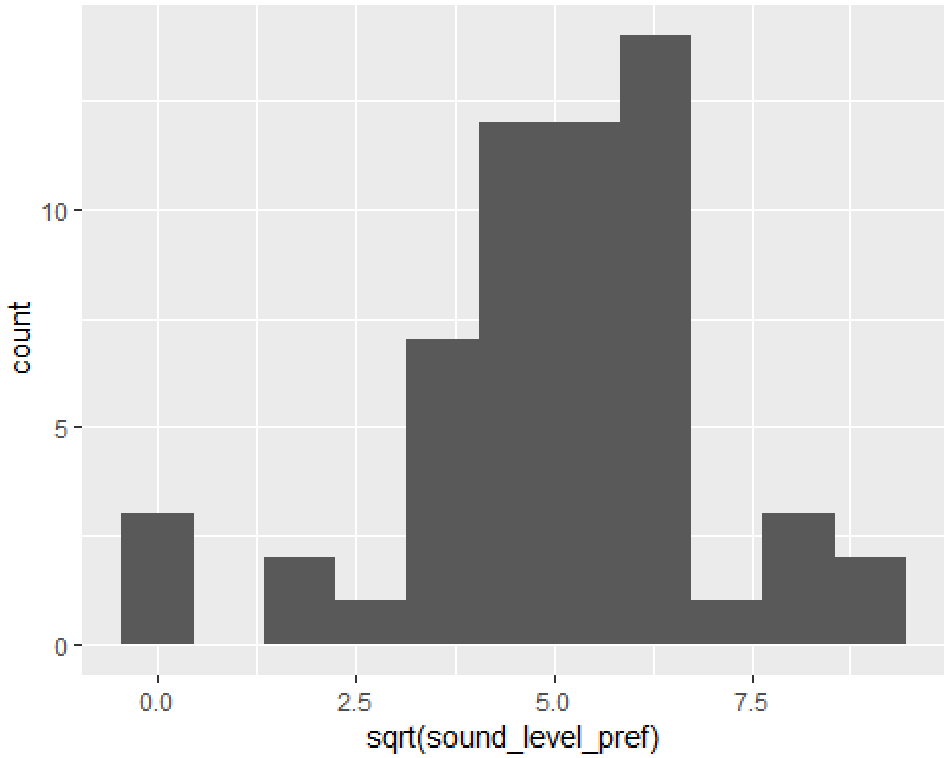
No relationship can be observed between music consumption and preference for volume in the two groups.

5) Are the volume preferences (sound_level_pref) normally distributed?

```
# making 3 different histograms to look for normal distribution
ggplot(df2,aes(sound_level_pref))+geom_histogram(binwidth = 8)
```




```
ggplot(df2,aes(sqrt(sound_level_pref)))+geom_histogram(binwidth=0.9)
```




```
#testing data
stat.desc(df$sound_level_pref, basic = FALSE, norm = TRUE)

##       median         mean      SE.mean CI.mean.0.95          var
##  25.00000000  28.89473684   2.42321740   4.85428777 334.70300752
##      std.dev     coef.var     skewness     skew.2SE     kurtosis
##  18.29489020   0.63315649   0.77490209   1.22484389   0.69857438
##     kurt.2SE   normtest.W   normtest.p
##   0.56053312   0.94545514   0.01230026

stat.desc(sqrt(df$sound_level_pref), basic = FALSE, norm = TRUE)

##       median         mean      SE.mean CI.mean.0.95          var
##   5.00000000   5.01186307   0.25966893   0.52017937   3.84339332
##      std.dev     coef.var     skewness     skew.2SE     kurtosis
##   1.96045743   0.39116340  -0.59210081  -0.93590024   0.59725874
##     kurt.2SE   normtest.W   normtest.p
##   0.47923788   0.95027757   0.02024644
```

conclusion:

Our data on the preference of sound level is positivily skewed and not normally distributed. This cannot be aided by transforming of the data: p>0.5.

```
# Script for a sample experiment that does the context reading task
#made by Peter Andreas Mikkelsen Thramkrongart

# import modules
from psychopy import visual, core, event,gui,data

#import panda
import pandas as pd

# import module for getting file names
import glob

# texts
text1 = '''
On a cold winter day I decided to go for a walk. I came to a path off the
main road and went that way.
The landscape became rough, with sharp rocks and steep hills. I climbed
over dead trees and waded through freezing water.
I was cold, cut, and bruised. There was many obstacles as I continued
forward.
I was ready to give up because I was wet and cold. Then out of nowhere came
a nice, open area.
Light was streaming down from the heaven and the open area had lots of
green grass and beautiful sunflowers.
I made it through my journey...
'''
text2 = '''
On a cold winter day I decided to go for a walk. I came to a path off the
main road and went that way.
The landscape became rough, with sharp rocks and steep hills. I climbed
over dead trees and waded through freezing water.
I was cold, cut, and bruised. There was many obstacles as I continued
forward.
I was ready to give up because I was wet and yodeling. Then out of nowhere
came a nice, open area.
Light was streaming down from the heaven and the open area had lots of
green grass and beautiful sunflowers.
I made it through my journey'''



# get date for unique file name
date=data.getDateStr()
# create an empty pandas data frame with column names relevant for your
# experiment, and put it somewhere early in the script
#columns = ["id", "age", "gender", "reaction_time"]
#DATA = pd.DataFrame(columns=columns)




# Create popup information box
dialog = gui.Dlg(title = "The journey")
dialog.addText("Please only write your given participant number and not
your name")#make sure people dont write letters
dialog.addField("Participant Number:")
dialog.addField("Age: ")
dialog.addField("Gender: ", choices=["Female", "Male",  "Other" ])
dialog.show()
if dialog.OK:
    ID = dialog.data
```

```
elif dialog.Cancel:
    core.quit()


#defining the text segmentation function
win = visual.Window(color="pink",fullscr=True)                      # define
window object

# define stop watch for reaction time measurement
stopwatch = core.Clock()

def text_fun(txt):                                     # define function
    columns = ["id", "age", "gender", "reaction_time","word"]
    DATA = pd.DataFrame(columns=columns)
    txt = txt.split()                                  # specify that we
want the text to be split up
    for i in txt:                                      # loop through the
words
        message = visual.TextStim(win, text = i,font="Comic Sans MS",
color=(-1.0,-1.0,-1.0))      # define text stimulus
        message.draw()                                 # draw stimulus
        win.flip()                                 # flip the window
        # start recording reaction time
        stopwatch.reset()
        # get reaction time
        reaction_time = stopwatch.getTime()
        # What does the dataframe contain?!
        DATA = DATA.append({
            'time_stamp': date,
            'id': ID[0],
            'age': ID[1],
            'gender': ID[2],
            "reaction_time": reaction_time,
            "word":i}, ignore_index = True)
            #only spacebar
        key=event.waitKeys(keyList = ["space", "escape"])[0]
# wait for key press
        if key=="escape":   # it's nice to be able to quit
            core.quit()
    #creating the logfile and putting it in "journey"
    logfile_name = "journey/logfile_{}_{}.csv".format(ID[0], date)
    # save the data frame
    DATA.to_csv(logfile_name)


#Welcome to the show
numberOnly=visual.TextStim(win,text='''
Welcome to the experiment!

In a moment, you will see a series of words that you have to read.
It is important that you understand the word in and the context before you
move on, and that yo u read consistently, since we measure your reading
time.
You submit your response by pressing any key to go to the next word.

Press any key when you are ready to begin the experiment.
''', color=(-1.0,-1.0,-1.0))
numberOnly.draw()
win.flip()
event.waitKeys()
```

```
#starting the experiment
#dividing participants into even and odd participant numbers
num = int(ID[0])
if (num % 2) == 0:
    text_fun(text1)
else:
    text_fun(text2)



#define window
win=visual.Window(color="black",fullscr=True)

# define stop watch for reaction time measurement
stopwatch = core.Clock()


#make end

end=visual.TextStim(win,text='''
The experiment is done.
Thank you for your participation.''')
end.draw()
win.flip()
event.waitKeys()

#P_LOADSTER bids you farewell
end1=visual.TextStim(win,text='''
P_LOADSTER bids you farewell''')
end1.draw()
win.flip()
event.waitKeys()
```

Portfolio 3: The Reading Experiment

Portfolio 3: The Reading Experiment

In this portfolio assignment, you will be conducting analyses of data from your reading experiment. The portfolio has two overall sections asking different questions:

1) A correlational section investigating what properties of words predict reading time,

2) an experimental section asking about the way our contextual expectations affect our reading time by contrasting two conditions.

1) What properties of words predict word-by-word reading time?

Conduct a minimum three correlational analyses where you investigate the relation between reading time and relevant predictors such as e.g. word length, frequencies, etc. Use the MRC database to provide relevant predictors of your own choice.

```
# code for correlational study 1 + plot

#create tibble with data
tbl <- c(even_df,steven_df)
tbl<- tbl%>% bind_rows()
#mhanging to uppercase to mach MRC database
tbl$word <- toupper(tbl$word)

#removing punctuation
tbl$word <- str_replace_all(tbl$word,"[:punct:]","")

#merging data
merged_RMC<- merge(baseData,tbl,key="word")

#checking for normal distribution
stat.desc(merged_RMC$reaction_time, basic=F,norm=T)

##       median         mean      SE.mean CI.mean.0.95          var
## 4.004800e-01 3.965648e-01 4.497173e-03 8.817839e-03 6.097707e-02
##      std.dev     coef.var     skewness     skew.2SE     kurtosis
## 2.469354e-01 6.226859e-01 2.542148e+00 2.850721e+01 3.559772e+01
##     kurt.2SE   normtest.W   normtest.p
## 1.996594e+02 8.409030e-01 7.521664e-48

#transforming  and checking data for normal distribution
stat.desc(log(merged_RMC$reaction_time), basic=F,norm=T)

##        median          mean       SE.mean  CI.mean.0.95           var
## -9.150914e-01 -2.368154e+00  6.832697e-02  1.339722e-01  1.407575e+01
##       std.dev      coef.var      skewness      skew.2SE      kurtosis
##  3.751767e+00 -1.584258e+00 -2.004738e+00 -2.248079e+01  2.108714e+00
##      kurt.2SE    normtest.W    normtest.p
##  1.182729e+01  5.119867e-01  6.060383e-68
```

```
stat.desc(sqrt(merged_RMC$reaction_time), basic=F,norm=T)

##        median          mean       SE.mean  CI.mean.0.95           var
##  6.328349e-01  5.729922e-01  4.758425e-03  9.330088e-03  6.826745e-02
##       std.dev      coef.var      skewness      skew.2SE      kurtosis
##  2.612804e-01  4.559930e-01 -1.082621e+00 -1.214033e+01  1.344881e+00
##      kurt.2SE    normtest.W    normtest.p
##  7.543126e+00  8.058289e-01  3.708379e-51

stat.desc((merged_RMC$reaction_time)^2, basic=F,norm=T)

##       median         mean      SE.mean CI.mean.0.95          var
## 1.603843e-01 2.182205e-01 8.902306e-03 1.745521e-02 2.389419e-01
##      std.dev     coef.var     skewness     skew.2SE     kurtosis
## 4.888168e-01 2.240013e+00 3.022972e+01 3.389910e+02 1.232237e+03
##     kurt.2SE   normtest.W   normtest.p
## 6.911334e+03 2.053554e-01 8.156197e-78

stat.desc((merged_RMC$reaction_time)/1, basic=F,norm=T)

##       median         mean      SE.mean CI.mean.0.95          var
## 4.004800e-01 3.965648e-01 4.497173e-03 8.817839e-03 6.097707e-02
##      std.dev     coef.var     skewness     skew.2SE     kurtosis
## 2.469354e-01 6.226859e-01 2.542148e+00 2.850721e+01 3.559772e+01
##     kurt.2SE   normtest.W   normtest.p
## 1.996594e+02 8.409030e-01 7.521664e-48

#removing deviation
sd_rt<- sd(merged_RMC$reaction_time)
fixed_sd_rt <- mean(sd_rt*3)


#removing deviation
merged_RMC<-subset(merged_RMC,reaction_time<fixed_sd_rt)

#checking for normal distribution. Now without deviation
stat.desc(merged_RMC$reaction_time, basic=F,norm=T)

##        median          mean       SE.mean  CI.mean.0.95           var
##  3.926096e-01  3.694004e-01  3.634107e-03  7.125717e-03  3.799577e-02
##       std.dev      coef.var      skewness      skew.2SE      kurtosis
##  1.949250e-01  5.276796e-01 -6.142407e-01 -6.728669e+00 -3.839309e-01
##      kurt.2SE    normtest.W    normtest.p
## -2.103605e+00  9.191847e-01  9.616011e-37

#transforming  and checking data for normal distribution
stat.desc(log(merged_RMC$reaction_time), basic=F,norm=T)

##        median          mean       SE.mean  CI.mean.0.95           var
## -9.349395e-01 -2.477320e+00  7.096055e-02  1.391387e-01  1.448684e+01
##       std.dev      coef.var      skewness      skew.2SE      kurtosis
##  3.806159e+00 -1.536402e+00 -1.936862e+00 -2.121726e+01  1.820224e+00
##      kurt.2SE    normtest.W    normtest.p
##  9.973231e+00  5.087453e-01  4.870790e-67

stat.desc(sqrt(merged_RMC$reaction_time), basic=F,norm=T)
```

```
##        median          mean       SE.mean  CI.mean.0.95           var
##  6.265857e-01  5.541382e-01  4.655414e-03  9.128286e-03  6.235288e-02
##       std.dev      coef.var      skewness      skew.2SE      kurtosis
##  2.497056e-01  4.506197e-01 -1.427686e+00 -1.563952e+01  7.499235e-01
##      kurt.2SE    normtest.W    normtest.p
##  4.108924e+00  7.559517e-01  3.475995e-54
```

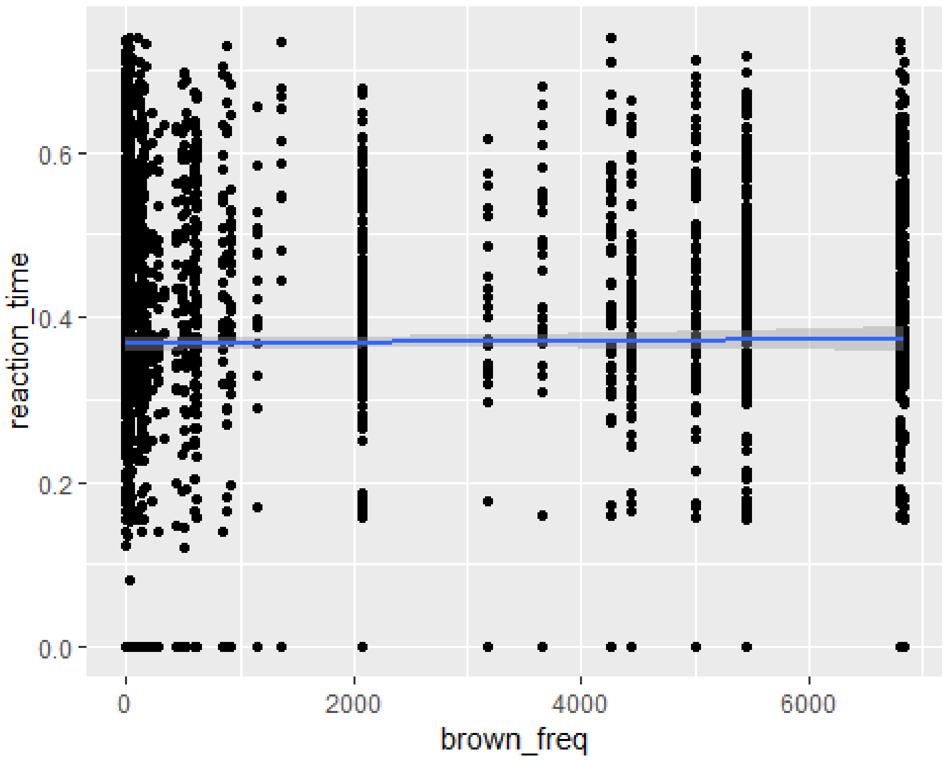
```
stat.desc((merged_RMC$reaction_time)^2, basic=F,norm=T)
```

```
##        median          mean       SE.mean  CI.mean.0.95           var
##  1.541423e-01  1.744392e-01  2.383880e-03  4.674286e-03  1.634965e-02
##       std.dev      coef.var      skewness      skew.2SE      kurtosis
##  1.278658e-01  7.330106e-01  5.250019e-01  5.751107e+00 -3.581528e-01
##      kurt.2SE    normtest.W    normtest.p
## -1.962363e+00  9.515001e-01  7.217284e-30
```

```
stat.desc((merged_RMC$reaction_time)/1, basic=F,norm=T)
```

```
##        median          mean       SE.mean  CI.mean.0.95           var
##  3.926096e-01  3.694004e-01  3.634107e-03  7.125717e-03  3.799577e-02
##       std.dev      coef.var      skewness      skew.2SE      kurtosis
##  1.949250e-01  5.276796e-01 -6.142407e-01 -6.728669e+00 -3.839309e-01
##      kurt.2SE    normtest.W    normtest.p
## -2.103605e+00  9.191847e-01  9.616011e-37
```

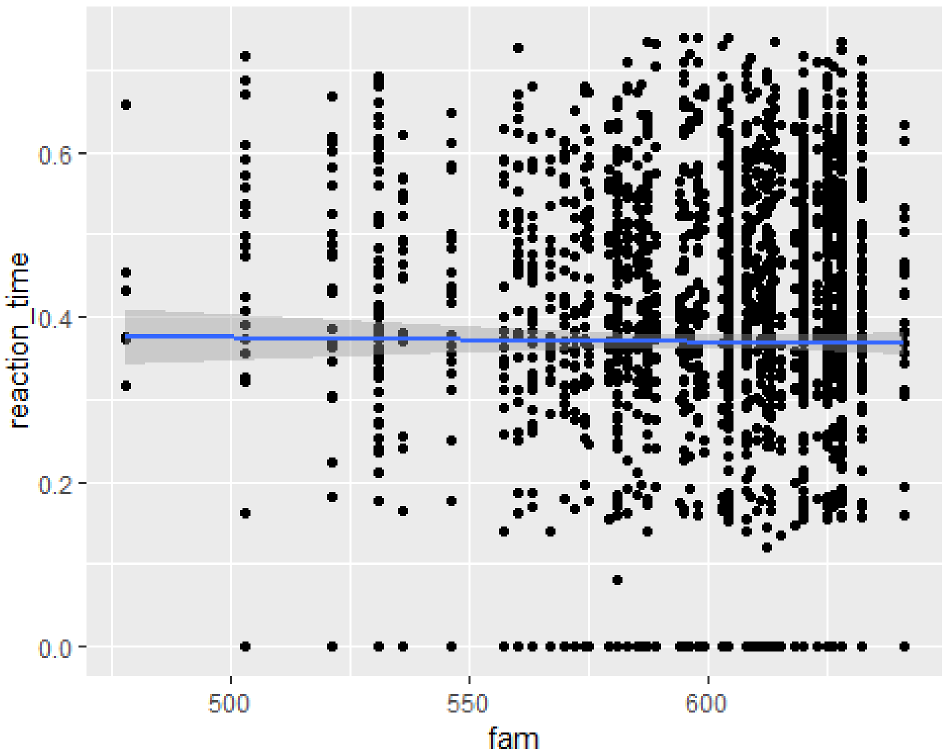
```
#hmmmm... nothing works. p-value is always lower than 0.05. Data is not no
rmally distributed.


#correlation check visually
ggplot(merged_RMC,aes(x=brown_freq,y=reaction_time))+geom_point()+geom_smo
oth(method=lm)
```




```
#test for correlation with spearman's test
cor.test(merged_RMC$reaction_time,merged_RMC$brown_freq, method="spearman"
)

## Warning in cor.test.default(merged_RMC$reaction_time, merged_RMC
## $brown_freq, : Cannot compute exact p-value with ties

##
##  Spearman's rank correlation rho
##
## data:  merged_RMC$reaction_time and merged_RMC$brown_freq
## S = 3909200000, p-value = 0.4199
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##        rho
## 0.01504299

#test for correlation with Kendallss test
cor.test(merged_RMC$reaction_time,merged_RMC$brown_freq, method="kendall")

##
##  Kendall's rank correlation tau
##
## data:  merged_RMC$reaction_time and merged_RMC$brown_freq
## z = 0.80542, p-value = 0.4206
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##        tau
## 0.01020368

#The p-value is above 0.05. There is no correlation.
```

The frequency of the words does not correlate with the reading time,*r* (13)=.15, *p*>0.05. You could expect a negative relationship. The more frequent the word, the shorter the reading time.

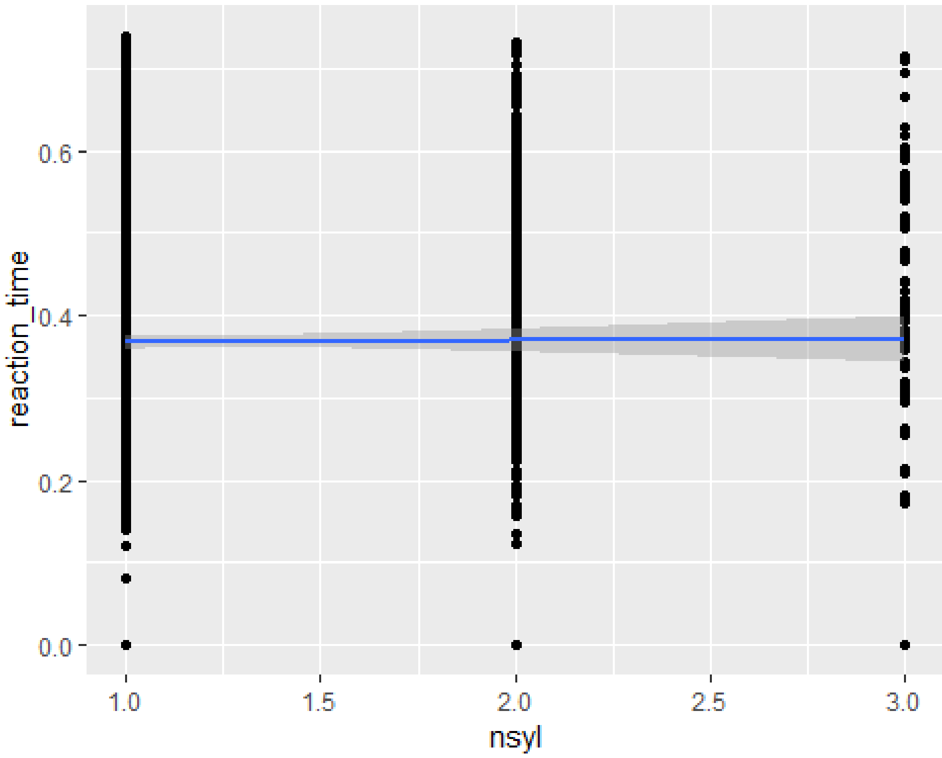
```
# code for correlational study 2 + plot
#fixing data
merged_RMC2 <-subset(merged_RMC,fam>0)

#test for correlation with Spearman's test
cor.test(merged_RMC2$reaction_time,merged_RMC2$fam, method="spearman")

## Warning in cor.test.default(merged_RMC2$reaction_time, merged_RMC2$fam,
 :
## Cannot compute exact p-value with ties

## 
##  Spearman's rank correlation rho
## 
## data:  merged_RMC2$reaction_time and merged_RMC2$fam
## S = 2474500000, p-value = 0.8945
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##         rho 
## 0.002675495

#test for correlation with Kendall's test
cor.test(merged_RMC2$reaction_time,merged_RMC2$fam, method="kendall")

## 
##  Kendall's rank correlation tau
## 
## data:  merged_RMC2$reaction_time and merged_RMC2$fam
## z = 0.12635, p-value = 0.8995
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##         tau 
## 0.001738091

#plotting data
ggplot(merged_RMC2,aes(x=fam,y=reaction_time))+geom_point()+geom_smooth(me
thod=lm)
```



The familiarity of the words does not correlate with the reading time,*r*(15)=.003 ,p>0.05. You could expect a negative relationship. The more familiar the word, the shorter the reading time.

```
# code for correlational study 3 + plot
#fixing data
merged_RMC3 <- subset(merged_RMC,nsyl>0)

#test for correlation with spearman's test
cor.test(merged_RMC3$reaction_time,merged_RMC3$nsyl, method="spearman")

## Warning in cor.test.default(merged_RMC3$reaction_time, merged_RMC3$nsyl
, :
## Cannot compute exact p-value with ties

##
##  Spearman's rank correlation rho
##
## data:  merged_RMC3$reaction_time and merged_RMC3$nsyl
## S = 2609700000, p-value = 0.6659
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##         rho
## 0.008623891

#test for correlation with Kendall's test
cor.test(merged_RMC3$reaction_time,merged_RMC3$nsyl, method="kendall")

##
##  Kendall's rank correlation tau
##
```

```
## data:  merged_RMC3$reaction_time and merged_RMC3$nsyl
## z = 0.43035, p-value = 0.6669
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##         tau
## 0.006926898

#plotting data
ggplot(merged_RMC3,aes(x=nsyl,y=reaction_time))+geom_point()+geom_smooth(m
ethod=lm)
```



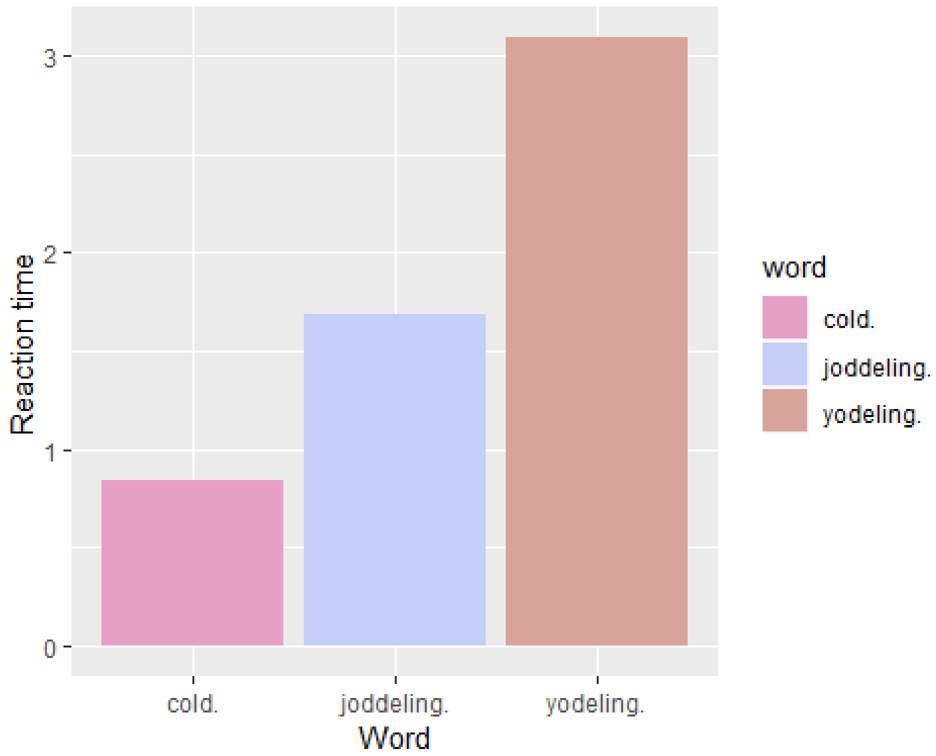
The number of syllables of a word does not correlate with the reading time,*r*(13)=.009, p>0.05. You could expect a positive relationship. The more syllables of a word, the longer the reading time.

2) How does contextual expectations affect reading time?

Conduct a contrastive analysis of the two conditions in your reading experiment. Single out reading time of the words that differ between the two versions of your text/story and compare the means using a t-test.

```
# code for your t-test study + plot

#read all the files into a tibble
evenTable <- even_df%>% bind_rows()
stevenTable<- steven_df%>% bind_rows()

#filtering the one word and fixing our problem with "cold."
filterEven <- filter(evenTable,word=="cold.")
```

```
filterSteven <- filter(stevenTable,X1==70)

#check for normal distribution
shapiro.test(filterEven$reaction_time)

##
##  Shapiro-Wilk normality test
##
## data:  filterEven$reaction_time
## W = 0.9622, p-value = 0.7305

#the p-value is above 0.05, so the data is normally distributed

shapiro.test(filterSteven$reaction_time)

##
##  Shapiro-Wilk normality test
##
## data:  filterSteven$reaction_time
## W = 0.88511, p-value = 0.08367

#the p-value is above 0.05, so the data is normally distributed

#data is normally distruted and a t-test for the independent variable will
, therefore, be conducted.
t.test(filterEven$reaction_time,filterSteven$reaction_time)

##
##  Welch Two Sample t-test
##
## data:  filterEven$reaction_time and filterSteven$reaction_time
## t = -2.1295, df = 13.69, p-value = 0.05187
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.044212425  0.004850405
## sample estimates:
## mean of x mean of y
## 0.4206485 0.9403295

#the p-value is above 0.05 and thus insignificant; there is no significant
 difference between the means of the two groups

filterEvenFilterSteven <-bind_rows(filterSteven,filterEven)

#making a bar plot (one of us made a spelling error with the word "yodelin
g/jodelling")
ggplot(filterEvenFilterSteven,aes(x=word,y=reaction_time,fill=word))+geom_
bar(stat="identity",position="dodge")+labs(x="Word",y="Reaction time ")+sc
ale_fill_manual(values=wes_palette("GrandBudapest2"))
```



Conclusion:

We don't see any significant differance in the reading time of a contextually fitting word and a contuxtually misfitting word, t(13.69)=-2.1295, $p>0.05$.

We expected a significant difference between the two conditions, but that does not seem to be the case in this experiment. We tosuspect that this is due to an inherent error in the experiment. participants get used to a certain rythm when pressing the button and may only comprehend the word afterwards. Maybe a significant effect would be visible with a larger and more diverse sample size. Also if the experiment was conducted with slower readers (maybe people with dyslexia or children) a significant difference would show.

Visual priming and reading time

Names
Christoffer Landberger (au605981@uni.au.dk)
Bianka Rumi (au603105@uni.au.dk)
Peter Andreas Mikkelsen Thramkrongart (au615814@ au.dk)
Eva Sahlholdt Hansen (au604018@uni.au.dk)
Kata Molnár (au603249@uni.au.dk)
School of Communication and Cognition, University of Aarhus,
Jens Chr. Skous Vej 2, 8000 Aarhus, Denmark

Abstract

This study examines the effect of visual priming on reading time. Participants were split up into three conditions: 1) Baseline condition with no visual priming, 2) Condition with visual priming non-related to the text given, and 3) Condition with visual priming related to the text given.
An ANOVA test was done, though with broken assumptions of normality of the residuals. However, the results show a significant effect driven by differences between the first condition and the third condition
The study is inconclusive and further research is required.

Keywords

Priming, reading time, spreading activation theory, cross-modality associations, visual priming

Introduction

This study examines whether there is a relation between how fast we recognize a topic (measured in reading time word-by-word) and whether or not we are prior primed with an image relevant to the text. The aim of the investigation is to explore whether associative spreading is likely to happen from one modality to another and if so whether it affects reaction time in recognition. Our hypothesis is that participants prior primed with an image relevant to the topic of the text, of which their reading time is measured, will read the first part of the text faster than those who are primed with an irrelevant image or not primed at all. The expected difference is due to associative spreading and faster retrieval of words from memory.

The experiment is inspired by prior theories on the topic of priming and associative spreading. Priming is understood as "[the concept] that environmental stimuli may affect subsequent responses by activating mental constructs without conscious realization" (Weingarten et al., 2016: 474). The spreading activation theory suggests that when we are primed to a certain context it facilitates faster recognition of associated material. An early study by Meyer and Schvaneveldt (1971) indicated that reaction time decreased in judging same-modality associations. Generally, priming seems to be most pronounced when the prime target and stimuli are in the same modality, but even though switching between modalities comes at a processing cost known as the *modality-switch effect* (Scerrati et al., 2015: 1f), there might still be some effect of cross-modality priming. Furthermore, there might be an effect on retrieval from memory when we are primed to what we are to retrieve (Anderson & behavior, 1983).

Materials and Methods

Participants

We collected data from 21 participants of a population consisting primarily of younger people with a mean age of 21.24 years. Most are university students, and of these, a considerable amount is bachelor students of Cognitive Science. The gender distribution is 64% female, 36% male. The only important inclusion criteria is a good mastery of English. Before deducting any result from this study to a wider population we need to take into consideration this demographic narrowness and the fact that our sample size may be too small to give a realistic representation of the whole population.

Of our participants 9 were given the first condition (i.e. baseline), 6 were given the second condition (figure 2), and 6 were given the third condition (figure 3).

Procedure and materials

The procedure of this experiment has only a few steps. We chose to use PsychoPy, an open-source software program specifically targeted towards usage for psychology-experiments. In this program, we created a script that ran a window in which the participants were to read a text of 147 words in a word-to-word manner (see box 1).
Reading time was measured by the time it took the participant to press a key to shift to the next word - a feature built into PsychoPy. The reason for our choosing of reading time as a measurement is because it is one of the most accurate methods to approach a measure of comprehension time (although it does have some limitations: see discussion).
Each participant was reading the text in one of the following three different priming conditions (the pictures was shown during the introduction text):

1) No priming (baseline condition)
2) Irrelevant priming (an image of the animation Shrek) (figure 2)
3) Relevant priming (an image of Hitler) (figure 3) [1]

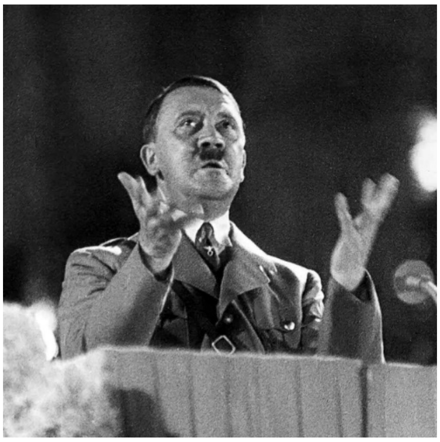
Because we noticed that participants usually got bored or tired during reading the text, we decided to look at the reaction time only during the first 50 words (based on our thoughts that the priming can be seen best at the beginning of the experiment). Thus, we expect a faster reading time for the first 50 words by participants under condition 3 than for participants under condition 1 or 2.

Box 1

"During their campaign in Poland, the Germans kept only 23 divisions in the west to guard their frontier against the French, who had nearly five times as many divisions mobilized. The French commander in chief proposed an advance against Germany through neutral Belgium and the Netherlands in order to have room to exercise his ponderous military machine. From October 1939 to March 1940, successive plans were developed for counteraction in the event of a German offensive through Belgium. The Germans would indeed have taken the route foreseen by the French if Hitler's desire for an offensive in November 1939 had not been frustrated, on the one hand, by bad weather and, on the other, by the hesitations of his generals. In March 1940 the bold suggestion that an offensive through the Ardennes should, be practicable for tank forces was adopted by Hitler, despite orthodox military opinion."[2]

Figure 2

Figure 3



Analysis

To analyze our data we used the programming language R.

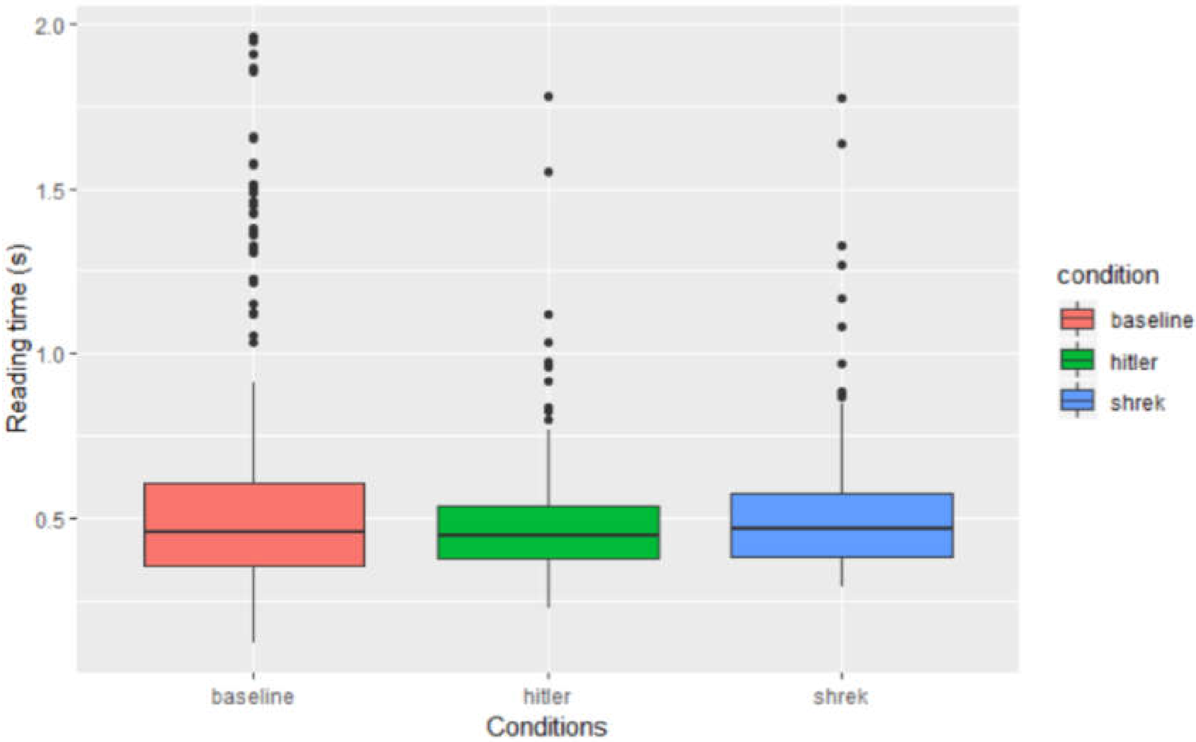
An ANOVA was conducted with reaction time as the outcome and the different types of visual priming as predictor variables. This was followed up by a pairwise Bonferroni corrected post-hoc test to examine whether or not there was a significant relation between the two.

We also conducted a bootstrapping of the data, due to the fact that the residuals are not normally distributed.
However, it was not possible with bootstrapping to transform the residuals (there was no normal distribution for the three conditions and basic reparations did not work).

Nonetheless, we tried to run an ANOVA analysis breaking the assumptions of normality of residuals. This means that even though we were able to document an effect of conditions regarding reaction times (see results), we cannot conclude anything from our data.

Results

We found a significant effect of the different conditions on the reaction times, between the baseline condition and the relevant priming condition, $F(2,1030) = 3.955$, $p=0.025$.



Graph 1: The figure shows a visual representation of our results of the experiment after removing outliers over 3 standard deviations away.

To examine the direction of the difference between the means of reading times for the different conditions, a pairwise t-test was made as a post hoc test (although, as mentioned it breaks the assumption of normality of residuals, and therefore we cannot conclude definitively from it).

The above results are also supported by the pairwise t-test which shows that there is a significant effect *($p<0.025$)* on the reading time (i.e. faster reading time) when the participants were primed with a picture of Hitler compared to the baseline.

Discussion

Even though our results indicate that there is a significant relationship between prior meaningful priming through images and reading time of a related text - and as a result, we are able to confirm our hypothesis - we cannot, due to broken assumptions mentioned in our analysis, conclude anything from this study.

There are several problems with our study.

1) Our collection of data was not performed in controlled environments, allowing many possible confounding factors to contaminate the data (noise, disturbance, time of day, unpreparedness, etc.).

2) Our population is very narrow. Our participant pool was only consisting of university students. Furthermore most of them are enrolled in the Cognitive Science program at Aarhus University, are very familiar with this sort of study, and in general, might not take this study too seriously in of itself.
3) Our population is too small (only 21 participants) and the sample sizes in each condition is not equal (distribution 9/6/6).
4) The study design itself, we suspect, is one of the major flaws of the experiment. Most participants seemed to get bored with the text (and to be honest it is rather dull) and thus click fast through it without comprehending (see 2)).
5) As we have mentioned previously, the assumption of normality of the residuals has been broken. Therefore we cannot conclude anything from our study.

Even though we cannot conclude anything from our study, it is certainly possible, looking at the results, that this study has made a type 1 error. Further research is therefore required.

References

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- Weingarten, E., Chen, Q., McAdams, M., Yi, J., Hepler, J., & Albarracín, D. J. P. B. (2016). From primed concepts to action: A meta-analysis of the behavioral effects of incidentally presented words.*142*(5), 472.

- Link to text used for the experiment: https://www.britannica.com/event/World-War-II/The-Baltic-states-and-the-Russo-Finnish-War-1939-40#ref511807

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[1]See literature for references to the chosen text and pictures.

[2]The text is a slightly edited version of a section from the online encyclopedia Britannica. See the list of literature.

The Sound Symbolism Experiment

Peter Andreas Mikkelsen Thramkrongart

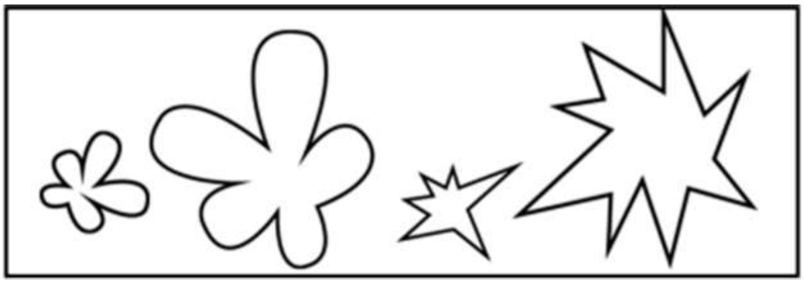
Abstract

This study examines the non-arbitrary mapping between speech sounds and the visual shape of objects known as the Bouba/Kiki effect. Participants were multiple times shown curved and jagged stimuli in two different sizes and asked to assign the names Kiki, Koko, Bibi, and Bobo to the stimuli. The data were analyzed with a logistic regression model. The study finds a significant effect with the consonant of the name predicting the shape of the stimuli, and a weaker effect of the vowel predicting the size of the stimuli.

Introduction

The aim of this study is to examine whether there is a relation between the mapping of speech sounds and the visual shape of objects and whether there is a relation between the mapping of speech sounds and the visual size of objects. Our hypothesis is that participants are significantly more likely to map the names with the consonant “k” to jagged objects and “b” to round shaped objects. We also hypothesize that participants are more likely to map names with the vowel “o” to the big objects and the vowel “I” to the smaller objects. The experiment was heavily inspired by the experiment conducted by Vilayanur S. Ramachandran and Edward Hubbard. Their study suggests that the naming of objects is not completely arbitrary. We wanted to expand on their experiment to investigate the mapping the names for size as well.

Materials and Methods



The study had 35 anonymous participants, whom multiple times were presented with the stimuli shown above. They asked to assign the names Koko, Kiki, Bibi, and Bobo to the visual objects. Because of the repeated measures in the study a mixed effects logistic regression model was chosen to model the data. We expected to see unsystematic variance due to the individual participants.

chosen as a predictor for the size with the participant ID as a dependent variable.

Analysis

The following mixed effects logistic regression models were chosen:

```
modelShape <- glmer(isJagged~ consonant+(1|id), kiki, family =
binomial)
```

shape~consonant+participant, family = binomial

The first model has the shape as the outcome variable, the consonant of the chosen word as the fixed effect and the participant as a random effect.

```
modelSize <- glmer(isBig~ vowel+(1|id), kiki, family = binomial)
```

size~vowel+participant, family = binomial

The second model has the vowel of the word

The second model has the size as the outcome variable, the vowel of the chosen word as the fixed effect and the participant as a random effect.

```
## # A tibble: 6 x 8
##      id stim_right    stim_left     word  consonant vowel shape  size
##   <dbl> <fct>         <fct>         <fct> <fct>     <fct> <fct>  <fct>
## 1    31 curved_big1   jagged_small2 KOKO  K         O     jagged sma
## 2    31 curved_big1   jagged_small1 KOKO  K         O     curved big
## 3    31 curved_small1 jagged_big2   KOKO  K         O     jagged big
## 4    31 curved_small2 jagged_big1   BIBI  B         I     curved sma
## 5    31 curved_small1 jagged_big2   BIBI  B         I     curved sma
## 6    31 curved_big2   jagged_small1 BIBI  B         I     curved big

#make GLMM models for shape

# define hypothesized models
modelShape <- glmer(isJagged~ consonant+(1|id), kiki, family = binomial)

modelSize <- glmer(isBig~ vowel+(1|id), kiki, family = binomial)

#make null-models

mNullShape <- glmer(isJagged ~ 1+(1|id), kiki, family = binomial)

mNullSize <- glmer(isBig ~ 1+(1|id), kiki, family = binomial)

# get model fit
anova(mNullShape, modelShape,test="Chisq")
```

```
## Data: kiki
## Models:
## mNullShape: isJagged ~ 1 + (1 | id)
## modelShape: isJagged ~ consonant + (1 | id)
##            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)

## mNullShape  2 1499.5 1509.5 -747.73   1495.5

## modelShape  3 1153.2 1168.2 -573.60   1147.2 348.26      1  < 2.2e-16 *
**
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(mNullSize, modelSize, test="Chisq")
```

```
## Data: kiki
## Models:
## mNullSize: isBig ~ 1 + (1 | id)
## modelSize: isBig ~ vowel + (1 | id)
##           Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)

## mNullSize  2 1511.7 1521.7 -753.83   1507.7

## modelSize  3 1497.1 1512.1 -745.56   1491.1 16.555      1  4.725e-05 **
*
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(modelShape)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: isJagged ~ consonant + (1 | id)
##    Data: kiki
##
##      AIC      BIC   logLik deviance df.resid
##   1153.2   1168.2   -573.6   1147.2     1085
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.5986 -0.4570 -0.4570  0.6255  2.1880
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  id     (Intercept) 0        0
## Number of obs: 1088, groups:  id, 34
##
## Fixed effects:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.5660     0.1134  -13.81   <2e-16 ***
## consonantK    2.5042     0.1482   16.90   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Correlation of Fixed Effects:
##            (Intr)
## consonantK -0.765
```

```
summary(modelSize)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: isBig ~ vowel + (1 | id)
##    Data: kiki
##
##      AIC      BIC   logLik deviance df.resid
##   1497.1   1512.1   -745.6   1491.1     1085
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.1597 -0.9052  0.8623  0.8623  1.1047
##
## Random effects:
##  Groups Name        Variance  Std.Dev.
##  id     (Intercept) 5.923e-14 2.434e-07
## Number of obs: 1088, groups:  id, 34
##
## Fixed effects:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.19919    0.08617  -2.311   0.0208 *
## vowelO       0.49545    0.12224   4.053 5.05e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##        (Intr)
## vowelO -0.705
```

```
#make data readible
boot::inv.logit(-1.5+2.5)#73%
```

```
## [1] 0.7310586
```

```
boot::inv.logit(-0.2+0.5)#57%
```

```
## [1] 0.5744425
```

```
#get odds ratio

exp(2.5)#12.182
```

```
## [1] 12.182
```

```
exp(0.5)#1.349
```

```
## [1] 1.349
```

Results

The model for shape significantly predicted whether predicted the outcome: $X^2(3, 1)$ =348.26, p = .002"

There is a significant relation between the choice of consonant for a visual object and the shape of the object.
shape: b = 2.5042 (SE = 0.1482), z =16.90, p < .002, odds ratio =
12.182

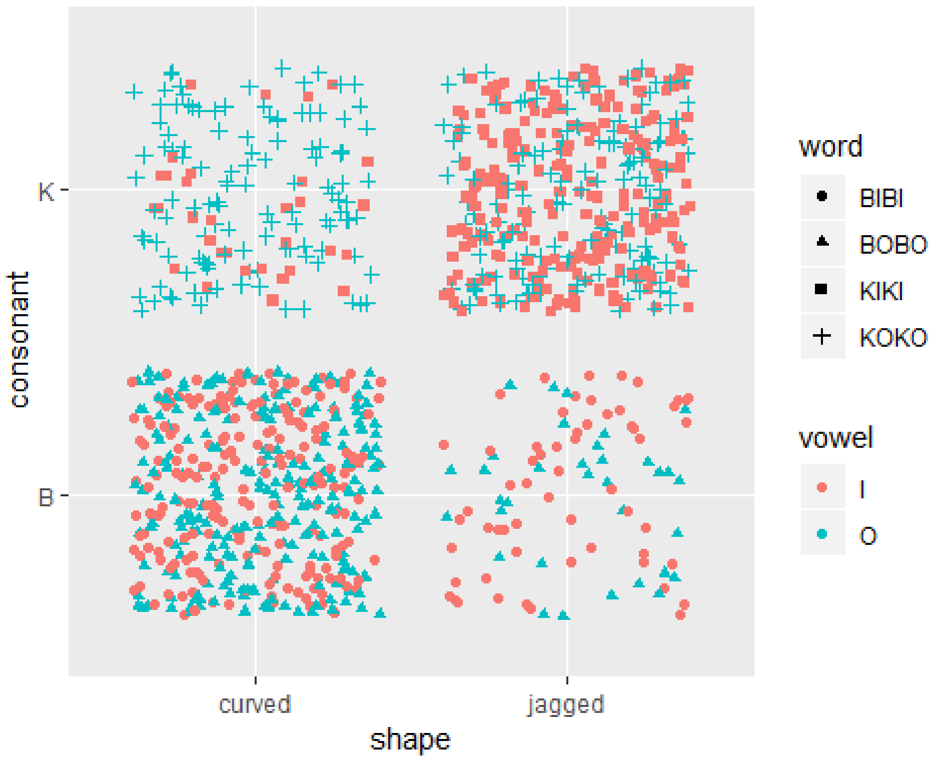
The model for size significantly predicted whether predicted the outcome: $X^2(3, 1)$ =16.555, p = .002"

There is a significant relation between the choice of a vowel for a visual object and the size o f the object.
size: b =0.49545 (SE =0.12224), z =4.053, p < .002, odds ratio =
1.349

Discussion

There is a significant effect between the consonant and the participant choice of shape akin to the bouba/kiki effect. A weaker effect between the vowel and the participant choice of size. Though it seems there is some confusion with the word "Koko". Maybe "Koko" is thought of as a cute name and therefore should be a small object. Further research will have to be made.

```
#visualise the data:
ggplot(kiki, aes(shape, consonant, color = vowel, shape = word)) + geom_ji
tter(width = .4, height = .4)
```


K
B
consonant
curved
jagged
shape
word
BIBI
BOBO
KIKI
KOKO
vowel
I
O