

# Numbers-Experiment-MML

Behavioural analysis

Swarnendu Moitra

## Table of contents

0.1 Plot . . . . .	6
--------------------	---

Analysis based on Persons experiment: Middleton and Moitra 2023

```
library("tidyverse")
library("plotrix")
library("lme4")
library("lmerTest")
library("report")
source('ggplot_theme_Publication-2.R')
```

```
# Load data
df_slet_1 <- read_csv("data/N72/slet.csv")
df_98zo_1 <- read_csv("data/N72/98zo.csv")
df_goty_1 <- read_csv("data/N72/goty.csv")
df_hebw_1 <- read_csv("data/N72/hebw.csv")
df_ajpl_1 <- read_csv("data/N72/ajpl.csv")
df_ld3j_1 <- read_csv("data/N72/ld3j.csv")

df_slet_2 <- read_csv("data/Rest/slet.csv")
df_98zo_2 <- read_csv("data/Rest/98zo.csv")
df_goty_2 <- read_csv("data/Rest/goty.csv")
df_hebw_2 <- read_csv("data/Rest/hebw.csv")
df_ajpl_2 <- read_csv("data/Rest/ajpl.csv")
df_ld3j_2 <- read_csv("data/Rest/ld3j.csv")

df_slet_3 <- read_csv("data/Rest_new/slet.csv")
df_98zo_3 <- read_csv("data/Rest_new/98zo.csv")
```

```

df_goty_3 <- read_csv("data/Rest_new/goty.csv")
df_hebw_3 <- read_csv("data/Rest_new/hebw.csv")
df_ajpl_3 <- read_csv("data/Rest_new/ajpl.csv")
df_ld3j_3 <- read_csv("data/Rest_new/ld3j.csv")

# Custom Function
data_cleaning <- function(arg1){
  arg1 <- arg1 %>%
    select(`Participant Private ID`, `Trial Number`, 'Tree Node Key', 'Reaction Time', Correct) %>%
    rename(Subject = `Participant Private ID`,
           Item = `Trial Number`,
           Condition = 'Tree Node Key',
           RT = 'Reaction Time',
           Accuracy = Correct) %>%
    filter(Screen == "Testing",
           `Response Type` == "response") %>%
    mutate(LogRT = log(RT))
  return(arg1)
}

## Use the custom function to clean the data

df_slet_1 <- data_cleaning(df_slet_1)
df_98zo_1 <- data_cleaning(df_98zo_1)
df_goty_1 <- data_cleaning(df_goty_1)
df_hebw_1 <- data_cleaning(df_hebw_1)
df_ajpl_1 <- data_cleaning(df_ajpl_1)
df_ld3j_1 <- data_cleaning(df_ld3j_1)

df_slet_2 <- data_cleaning(df_slet_2)
df_98zo_2 <- data_cleaning(df_98zo_2)
df_goty_2 <- data_cleaning(df_goty_2)
df_hebw_2 <- data_cleaning(df_hebw_2)
df_ajpl_2 <- data_cleaning(df_ajpl_2)
df_ld3j_2 <- data_cleaning(df_ld3j_2)

df_slet_3 <- data_cleaning(df_slet_3)
df_98zo_3 <- data_cleaning(df_98zo_3)
df_goty_3 <- data_cleaning(df_goty_3)
df_hebw_3 <- data_cleaning(df_hebw_3)
df_ajpl_3 <- data_cleaning(df_ajpl_3)
df_ld3j_3 <- data_cleaning(df_ld3j_3)

```

```

data <- rbind(df_slet_1,df_98zo_1,df_goty_1,df_hebw_1,df_ajpl_1,df_ld3j_1,
             df_slet_2,df_98zo_2,df_goty_2,df_hebw_2,df_ajpl_2,df_ld3j_2
             #df_slet_3,df_98zo_3,df_goty_3,df_hebw_3,df_ajpl_3,df_ld3j_3
             )

## Create the summary
data_group <- data %>% group_by(Condition) %>% summarise(RT_mean=mean(RT),RT_SE=std.error(RT))

Data <- data
summary(Data)

```

Subject	Item	Condition	RT
Min. : 9898448	Min. : 1.00	Length:10608	Min. : 16.63
1st Qu.: 9991270	1st Qu.:12.75	Class :character	1st Qu.: 1749.92
Median : 9992609	Median :24.50	Mode :character	Median : 3241.49
Mean : 9982939	Mean :24.50		Mean : 5158.65
3rd Qu.: 9994705	3rd Qu.:36.25		3rd Qu.: 5978.85
Max. :10006213	Max. :48.00		Max. :158673.60
Accuracy	Spreadsheet: display	Screen	Task Name
Min. :0.000	Length:10608	Length:10608	Length:10608
1st Qu.:0.000	Class :character	Class :character	Class :character
Median :1.000	Mode :character	Mode :character	Mode :character
Mean :0.629			
3rd Qu.:1.000			
Max. :1.000			
Response Type	LogRT		
Length:10608	Min. : 2.811		
Class :character	1st Qu.: 7.467		
Mode :character	Median : 8.084		
	Mean : 7.986		
	3rd Qu.: 8.696		
	Max. :11.975		

#Stats

```

HP_data <- data %>%
  mutate(
    Subject = as.factor(Subject),
    Condition = as.factor(Condition),
    Item = as.factor(Item)
    #Cond_Type = as.factor(Cond_Type),
  )

```

```

    #Response = as.factor(Response)
  )
str(HP_data)

```

```

tibble [10,608 x 10] (S3: tbl_df/tbl/data.frame)
 $ Subject      : Factor w/ 221 levels "9898448","9898449",...: 13 13 13 13 13 13 13 13 13 13 ...
 $ Item         : Factor w/ 48 levels "1","2","3","4",...: 1 2 3 4 5 6 7 8 9 10 ...
 $ Condition    : Factor w/ 6 levels "task-98zo","task-ajpl",...: 6 6 6 6 6 6 6 6 6 6 ...
 $ RT          : num [1:10608] 10352 4506 6214 5762 7446 ...
 $ Accuracy     : num [1:10608] 1 1 1 1 1 1 1 1 1 1 ...
 $ Spreadsheet: display: chr [1:10608] "Testing02" "Testing02" "Testing02" "Testing02" ...
 $ Screen       : chr [1:10608] "Testing" "Testing" "Testing" "Testing" ...
 $ Task Name    : chr [1:10608] "1e-1i B Testing" "1e-1i B Testing" "1e-1i B Testing" ...
 $ Response Type: chr [1:10608] "response" "response" "response" "response" ...
 $ LogRT        : num [1:10608] 9.24 8.41 8.73 8.66 8.92 ...

```

```

RT_model_1 <- lmer(LogRT ~ Condition + (1|Subject) + (1|Item), data = HP_data, REML = F)
summary(RT_model_1)

```

Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's method [lmerModLmerTest]

Formula: LogRT ~ Condition + (1 | Subject) + (1 | Item)  
Data: HP\_data

AIC	BIC	logLik	deviance	df.resid
20732.2	20797.6	-10357.1	20714.2	10599

Scaled residuals:

Min	1Q	Median	3Q	Max
-9.6906	-0.5697	-0.0638	0.5104	7.3289

Random effects:

Groups	Name	Variance	Std.Dev.
Subject	(Intercept)	0.7382	0.8592
Item	(Intercept)	0.1277	0.3573
Residual		0.3679	0.6066

Number of obs: 10608, groups: Subject, 221; Item, 48

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t )
(Intercept)	8.1802	0.1712	254.7636	47.790	<2e-16 ***

Conditiontask-ajpl	-0.1761	0.2151	220.8044	-0.819	0.4139
Conditiontask-goty	-0.3840	0.2079	220.8044	-1.847	0.0661
Conditiontask-hebw	-0.1464	0.2151	220.8044	-0.680	0.4969
Conditiontask-ld3j	-0.1779	0.2151	220.8044	-0.827	0.4091
Conditiontask-slet	-0.1946	0.2204	220.8044	-0.883	0.3783

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	Cndtntsk-j	Cndtntsk-g	Cndtntsk-h	Cndt-3
Cndtntsk-jp	-0.724				
Cndtntsk-gt	-0.749	0.596			
Cndtntsk-hb	-0.724	0.576	0.596		
Cndtntsk-l3	-0.724	0.576	0.596	0.576	
Cndtntsk-sl	-0.706	0.562	0.581	0.562	0.562

```
ACC_model_1 <- glmer(Accuracy ~ Condition + (1|Subject) + (1|Item), data = HP_data, family =
summary(ACC_model_1)
```

Generalized linear mixed model fit by maximum likelihood (Laplace  
Approximation) [glmerMod]

Family: binomial (logit)

Formula: Accuracy ~ Condition + (1 | Subject) + (1 | Item)

Data: HP\_data

AIC	BIC	logLik	deviance	df.resid
13403.1	13461.3	-6693.6	13387.1	10600

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.1499	-1.0355	0.5338	0.7934	1.5746

Random effects:

Groups	Name	Variance	Std.Dev.
Subject	(Intercept)	0.4869742	0.69784
Item	(Intercept)	0.0009203	0.03034

Number of obs: 10608, groups: Subject, 221; Item, 48

Fixed effects:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	0.6338	0.1453	4.361	1.29e-05 ***
Conditiontask-ajpl	-0.2003	0.1911	-1.048	0.295

Conditiontask-goty	-0.1563	0.1846	-0.847	0.397
Conditiontask-hebw	0.2270	0.1918	1.183	0.237
Conditiontask-ld3j	-0.1341	0.1911	-0.702	0.483
Conditiontask-slet	0.1027	0.1964	0.523	0.601

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	Cndtntsk-j	Cndtntsk-g	Cndtntsk-h	Cndt-3
Cndtntsk-jp	-0.759				
Cndtntsk-gt	-0.786	0.598			
Cndtntsk-hb	-0.756	0.575	0.595		
Cndtntsk-l3	-0.759	0.577	0.598	0.575	
Cndtntsk-sl	-0.738	0.562	0.581	0.560	0.562

## 0.1 Plot

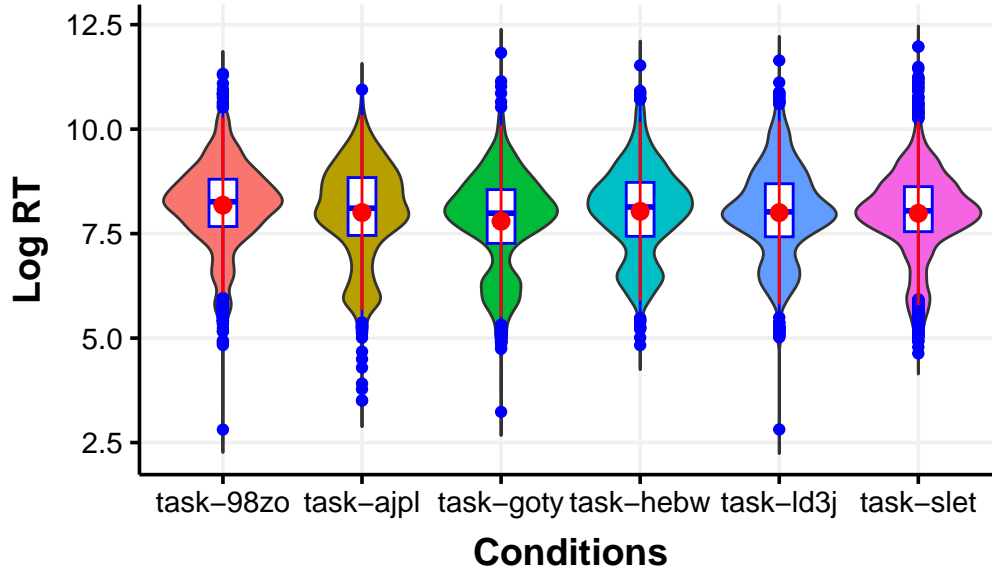
```
Data$Condition <- as.factor(Data$Condition)

RT <- ggplot(Data, aes(x=Condition, y=LogRT)) +
  geom_violin(aes(fill = Condition), trim = FALSE, show.legend = FALSE) +
  ylab("Log RT") +
  xlab("Conditions") +

  # geom_signif(
  #   comparisons = list(c("Grammatical", "Pseudowords")),
  #   margin_top = 0.20,
  #   step_increase = 0.05,
  #   tip_length = 0.01,
  #   map_signif_level = TRUE
  # )+
  theme_Publication()+

  # Add geom_boxplot() to include box plot
  geom_boxplot(width = 0.2, fill = "white", color = "blue")

RT + stat_summary(fun.data=mean_sdl, mult=1,
  geom="pointrange", color="red")
```

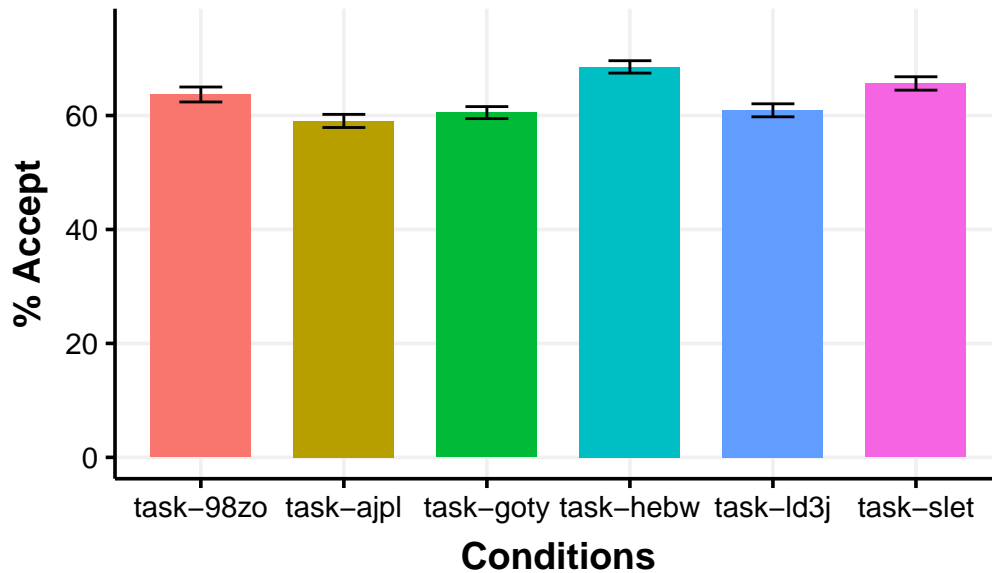


```
ACC_plot<- ggplot(data_group,
                  aes(x=Condition,y=ACC,fill=Condition)) +

# geom_bar function is used to plot bars of barplot
geom_bar(stat = "identity", width = 0.7, position = position_dodge(0.7), show.legend = FALSE) +
#scale_x_discrete(limits = Conditions) + facet_wrap( ~Prefix) +
ylab("% Accept") +
xlab("Conditions") +
theme_Publication()+
coord_cartesian(ylim = c(0, 75)) +
# scale_y_continuous(expand = expansion(mult = c(0, 0.05)))+
# geom_signif(
#   comparisons = list(c("Grammatical", "Pseudowords")),
#   margin_top = 0.12,
#   step_increase = 0.09,
#   tip_length = 0.05,
#   annotation = c("***")
# )+

#geom_errorbar function is used to plot error bars
geom_errorbar(aes(ymin=ACC-ACC_SE,
                  ymax=ACC+ACC_SE,
                  width=0.3))
```

```
ACC_plot
```



```
report(ACC_model_1)
```

We fitted a logistic mixed model (estimated using ML and Nelder-Mead optimizer) to predict Accuracy with Condition (formula: Accuracy ~ Condition). The model included Subject as random effects (formula: list(~1 | Subject, ~1 | Item)). The model's total explanatory power is moderate (conditional R<sup>2</sup> = 0.13) and the part related to the fixed effects alone (marginal R<sup>2</sup>) is of 6.38e-03. The model's intercept, corresponding to Condition = task-98zo, is at 0.63 (95% CI [0.35, 0.92], p < .001). Within this model:

- The effect of Condition [task-ajpl] is statistically non-significant and negative (beta = -0.20, 95% CI [-0.57, 0.17], p = 0.295; Std. beta = -0.20, 95% CI [-0.57, 0.17])
- The effect of Condition [task-goty] is statistically non-significant and negative (beta = -0.16, 95% CI [-0.52, 0.21], p = 0.397; Std. beta = -0.16, 95% CI [-0.52, 0.21])
- The effect of Condition [task-hebw] is statistically non-significant and positive (beta = 0.23, 95% CI [-0.15, 0.60], p = 0.237; Std. beta = 0.23, 95% CI [-0.15, 0.60])
- The effect of Condition [task-ld3j] is statistically non-significant and



negative (beta = -0.13, 95% CI [-0.51, 0.24], p = 0.483; Std. beta = -0.13, 95% CI [-0.51, 0.24])

- The effect of Condition [task-slet] is statistically non-significant and positive (beta = 0.10, 95% CI [-0.28, 0.49], p = 0.601; Std. beta = 0.10, 95% CI [-0.28, 0.49])

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation.