# FLO replication - Preprocessing and analysis

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## Contents

# clean WS, set WD

```
rm(list = ls());
```

Set your local working directory. This should be (and is assumed to be in the rest of the code) the highest point in your local folder:

```r
localGitDir <- 'C:/Users/eva_v/Documents/GitHub/leverhulmeNDL'
#setwd(localGitDir);
```

```r
fribbleSet <- read.csv(paste(localGitDir, "/exp1/stimuli/stimuli.csv", sep = ""),
                       header = T,
                       colClasses=c("cueID"="factor",
                        "bodyShape"="factor",
                        "label"="factor",
                        "fribbleID"="factor"
                        ));
```

## Load functions from the lab repo

```r
urlFolder <- 'https://api.github.com/repos/n400peanuts/languagelearninglab/git/trees/master?recursive=1
urlRaw <- 'https://raw.githubusercontent.com/n400peanuts/languagelearninglab/master/tools/'

source('C:/Users/eva_v/Documents/languagelearninglab/tools/loadFunctionsGithub.R')

loadFunctionsGithub(urlFolder = urlFolder, urlRaw = urlRaw);
```

```
## [1] "----loading. Please wait----"
```

```r
rm(urlFolder, urlRaw)
```

## Check stimuli set

It's important to check that every fribble is unique in the way its features are assembled within each category. Feature position and identity are coded into cueID.

I'm going to check whether the combination of cues used to build the fribble is unique by filtering for n > 1:

```r
fribbleSet %>%
  group_by(category, cueID) %>%
  count() %>%
  filter(n > 1);
```

```
## Warning: Factor `cueID` contains implicit NA, consider using
## `forcats::fct_explicit_na`
```

```
## # A tibble: 0 x 3
## # Groups:   category, cueID [1]
## # ... with 3 variables: category <int>, cueID <fct>, n <int>
```

Great, each Fribble is unique!

## Load data

List the files present in the folder, and load them.

```
df <- list.files(paste(localGitDir, "/exp1/data/", sep = ""));
```

We have 4 files.

```
for (i in 1:length(df)){
  gsub(".csv$", "", df[i]) -> id
  assign(id, data.frame())
  read.csv(paste(localGitDir, "/exp1/data/", df[i], sep = ""),
           na.strings=c("","NA"),
           colClasses=c("presentedLabel"="factor",
                        "presentedImage"="factor",
                        "learningType"="factor",
                        "Trial.Type"="factor",
                        "Test.Part"="factor",
                        "Key.Press"="factor"
                        ))-> temp
  assign(paste0(id), temp)
};

rm(temp, df, i, id);
```

The dataset name is decided autonomously by Gorilla. Importantly, Gorilla produces a different file per condition, and codes the conditions by the last 4 letters.

- 2yjh is the FL learning
- q8hp is the LF learning

I'm going to rename them for clarity.

```
dataFL<-`data_exp_15519-v13_task-2yjh`
dataFL2<-`data_exp_15519-v14_task-2yjh`

rm(`data_exp_15519-v13_task-2yjh`)
rm(`data_exp_15519-v14_task-2yjh`)

dataLF <- `data_exp_15519-v13_task-q8hp`
dataLF2 <- `data_exp_15519-v14_task-q8hp`

rm(`data_exp_15519-v13_task-q8hp`)
rm(`data_exp_15519-v14_task-q8hp`)
```

```
rbind(dataFL, dataFL2)-> dataFL
rbind(dataLF, dataLF2)-> dataLF

rm(dataFL2, dataLF2)
```

Gorilla's output is extremely messy. Each row is a screen event. However, we want only the events related to 1. the presentations of the fribbles and the labels 2. participants' response and 3. what type of tasks.

I have coded these info in some columns and rows that I'm going to select:

```
raw_dataFL<- dataFL[c('Participant.Private.ID', 'learningType', 'Test.Part' ,
         'presentedImage', 'presentedLabel', 'Reaction.Time', "Key.Press",
          'Trial.Type', 'Trial.Index', 'Correct')]

raw_dataLF<- dataLF[c('Participant.Private.ID', 'learningType', 'Test.Part' ,
         'presentedImage', 'presentedLabel', 'Reaction.Time', "Key.Press",
          'Trial.Type', 'Trial.Index', 'Correct')]
```

Select rows:

```
rowsIwantTokeep <- c("learningBlock1", "learningBlock2", "learningBlock3",
                        "learningBlock4", "generalizationPL", "generalizationLP",
                        "randomDot", "contingencyJudgement")

raw_dataFL <- raw_dataFL %>%
  filter(Test.Part %in% rowsIwantTokeep ) %>%
  rename(subjID = Participant.Private.ID,
         learning = learningType,
         task = Test.Part,
         fribbleID = presentedImage,
         label = presentedLabel,
         rt = Reaction.Time,
         resp = Key.Press,
         trialType = Trial.Type,
         trialIndex = Trial.Index,
         acc = Correct)

raw_dataLF <- raw_dataLF %>%
  filter(Test.Part %in% rowsIwantTokeep ) %>%
  rename(subjID = Participant.Private.ID,
         learning = learningType,
         task = Test.Part,
         fribbleID = presentedImage,
         label = presentedLabel,
         rt = Reaction.Time,
         resp = Key.Press,
         trialType = Trial.Type,
         trialIndex = Trial.Index,
         acc = Correct)

rm(rowsIwantTokeep, dataFL, dataLF);
```

I'm going to merge both datasets, FL and LF, because we have anyway a column "learning" that can tell us which one is which.

```
rbind(raw_dataFL, raw_dataLF)-> raw_data;
rm(raw_dataFL, raw_dataLF);
```

# Check learning

Let's filter and check learning trials:

```
learningBlocks <- c("learningBlock1", "learningBlock2", "learningBlock3", "learningBlock4");

learning <- raw_data %>%
  filter(task %in% learningBlocks)

learning <- droplevels(learning);
rm(learningBlocks)
```

## How many trials per participant?

```
learning %>%
  group_by(subjID, learning) %>%
  count()
```

```
## # A tibble: 80 x 3
## # Groups:   subjID, learning [80]
##     subjID learning     n
##      <int> <fct>    <int>
##  1 1414932 LF         120
##  2 1414933 LF         120
##  3 1414937 FL         120
##  4 1414945 FL         120
##  5 1414957 FL         120
##  6 1415040 FL         120
##  7 1420163 FL         120
##  8 1420165 FL         120
##  9 1420169 LF         120
## 10 1420171 LF         120
## # ... with 70 more rows
```

Great, 120 trials per participant, per learning.

Let's check whether the blocks' length varied across participants:

```
learning %>%
  group_by(subjID, task) %>%
  count()
```

```
## # A tibble: 320 x 3
## # Groups:   subjID, task [320]
##     subjID task               n
##      <int> <fct>          <int>
##  1 1414932 learningBlock1    21
##  2 1414932 learningBlock2    28
##  3 1414932 learningBlock3    47
##  4 1414932 learningBlock4    24
##  5 1414933 learningBlock1    26
```

```
##   6 1414933 learningBlock2    22
##   7 1414933 learningBlock3    44
##   8 1414933 learningBlock4    28
##   9 1414937 learningBlock1    27
##  10 1414937 learningBlock2    47
## # ... with 310 more rows
```

Great! Each participant had a different amount of trials distributed across blocks. That's important because our random dot task was presented at the end of each block, and we wanted its presentation to be unpredictable. Anyway, the sum of all the learning trials was always 120.

### Did we assign our learning randomly every couple of people?

```
table(learning$subjID, learning$learning)
```

```
##
##            FL  LF
##   1414932   0 120
##   1414933   0 120
##   1414937 120   0
##   1414945 120   0
##   1414957 120   0
##   1415040 120   0
##   1420163 120   0
##   1420165 120   0
##   1420169   0 120
##   1420171   0 120
##   1420177 120   0
##   1420180 120   0
##   1420185   0 120
##   1420199 120   0
##   1420204   0 120
##   1420552   0 120
##   1420573   0 120
##   1420577   0 120
##   1420580 120   0
##   1420622 120   0
##   1422463 120   0
##   1422465 120   0
##   1422466 120   0
##   1422467   0 120
##   1422470   0 120
##   1422472 120   0
##   1422473   0 120
##   1422475   0 120
##   1422476   0 120
##   1422477 120   0
##   1422675 120   0
##   1422676   0 120
##   1422677 120   0
##   1422678   0 120
```

```
##    1422679 120   0
##    1422680   0 120
##    1422681   0 120
##    1422689 120   0
##    1422715   0 120
##    1422716 120   0
##    1431942   0 120
##    1431944 120   0
##    1431946 120   0
##    1431948   0 120
##    1431949 120   0
##    1431952   0 120
##    1431953 120   0
##    1431954   0 120
##    1431956   0 120
##    1431957 120   0
##    1431958 120   0
##    1431959   0 120
##    1431960   0 120
##    1431961 120   0
##    1431963   0 120
##    1431965 120   0
##    1431966   0 120
##    1431968   0 120
##    1431969 120   0
##    1431970   0 120
##    1431972 120   0
##    1431974 120   0
##    1431978 120   0
##    1431979 120   0
##    1431981   0 120
##    1431984 120   0
##    1431989   0 120
##    1431992 120   0
##    1431997 120   0
##    1431998   0 120
##    1431999   0 120
##    1432003   0 120
##    1432007   0 120
##    1432009 120   0
##    1432011 120   0
##    1432030   0 120
##    1432052 120   0
##    1432075 120   0
##    1432301   0 120
##    1432323   0 120
```

Kind of. After chicking with Gorilla's suppoert: apparently, if a participant access Gorilla, but it's not allowed to start the experiment (e.g., the browser is not suitable), or leaves the session, this counts anyway for the randomisation.

The rows related to the presentation of fribbles and labels, inherit Gorilla's http address of where they are stored. Nothing I can do to change this in Gorilla, but we can clean the rows by those info like this:

```r
as.factor(gsub("/task/70033/56/asset/|/task/70033/57/asset/", "", learning$fribbleID))-> learning$fribbl
as.factor(gsub(".jpg$", "", learning$fribbleID))-> learning$fribbleID

as.factor(gsub("/task/70033/56/asset/|/task/70033/57/asset/", "", learning$label))-> learning$label
as.factor(gsub(".mp3$", "", learning$label))-> learning$label
learning$resp <- as.factor('NA')
```

This is how the learning dataframe looks like now:

```r
head(learning);
```

```
##    subjID learning          task fribbleID label rt resp
## 1 1414937       FL learningBlock1     20375 FLbim NA   NA
## 2 1414937       FL learningBlock1     31075 FLtob NA   NA
## 3 1414937       FL learningBlock1     32775 FLtob NA   NA
## 4 1414937       FL learningBlock1     32875 FLtob NA   NA
## 5 1414937       FL learningBlock1     22025 FLbim NA   NA
## 6 1414937       FL learningBlock1     10425 FLdep NA   NA
##                trialType trialIndex acc
## 1 audio-keyboard-response         22  NA
## 2 audio-keyboard-response         25  NA
## 3 audio-keyboard-response         28  NA
## 4 audio-keyboard-response         31  NA
## 5 audio-keyboard-response         34  NA
## 6 audio-keyboard-response         37  NA
```

```r
summary(learning);
```

```
##      subjID        learning              task        fribbleID      label     
##  Min.   :1414932   FL:4920   learningBlock1:2283   10975   :  86   FLbim:1640  
##  1st Qu.:1422003   LF:4680   learningBlock2:2549   22575   :  84   FLdep:1640  
##  Median :1427329             learningBlock3:2336   31975   :  84   FLtob:1640  
##  Mean   :1426320             learningBlock4:2432   32675   :  84   LFbim:1560  
##  3rd Qu.:1431971                                   21875   :  82   LFdep:1560  
##  Max.   :1432323                                   30375   :  82   LFtob:1560  
##                                                    (Other):9098               
##        rt          resp                        trialType      trialIndex 
##  Min.   : 12.36   NA:9600   audio-keyboard-response:4920   Min.   : 22  
##  1st Qu.: 52.50             image-keyboard-response:4680   1st Qu.:115  
##  Median : 88.00                                            Median :211  
##  Mean   :126.25                                            Mean   :211  
##  3rd Qu.:214.71                                            3rd Qu.:307  
##  Max.   :249.00                                            Max.   :400  
##  NA's   :9593                                                           
##       acc      
##  Min.   : NA   
##  1st Qu.: NA   
##  Median : NA   
##  Mean   :NaN   
##  3rd Qu.: NA   
##  Max.   : NA   
##  NA's   :9600  
```

Our fribbles were presented two times during learning.

### Check if fribbles are presented > 2 times:

```
learning %>%
  group_by(subjID, fribbleID) %>%
  count() %>%
  filter(n >2)
```

```
## Warning: Factor `fribbleID` contains implicit NA, consider using
## `forcats::fct_explicit_na`
```

```
## # A tibble: 0 x 3
## # Groups:   subjID, fribbleID [1]
## # ... with 3 variables: subjID <int>, fribbleID <fct>, n <int>
```

None, perfect.

### Check whether there are fribbles presented only once:

```
learning %>%
  group_by(subjID, fribbleID) %>%
  count() %>%
  filter(n < 2)
```

```
## Warning: Factor `fribbleID` contains implicit NA, consider using
## `forcats::fct_explicit_na`
```

```
## # A tibble: 0 x 3
## # Groups:   subjID, fribbleID [1]
## # ... with 3 variables: subjID <int>, fribbleID <fct>, n <int>
```

Perfect.

### Check the association between the fribbles and the labels (high and low frequency with the correct labels)

Fribbles ID are coded in this way: e.g., 10175-> [1] is the category [01] is the number of the fribble [75] is the frequency.

In the column fribbleID we have the fribble presented, in the column label we have the sound played.

Association between fribbles and labels are fixed:

- category 1, regardless of the frequency, has the label: dep
- category 2, regardless of the frequency, has the label: bim
- category 3, regardless of the frequency, has the label: tob

I'm going to add a column for category, fribble number, and frequency, in order to check whether everything is okay:

We should have only 3 categories, presented twice per participant. Each category is made of 20 exemplars.

```
learning$category <- 0
learning[substr(as.character(learning$fribbleID), 1, 1)==1,]$category <- 1
learning[substr(as.character(learning$fribbleID), 1, 1)==2,]$category <- 2
learning[substr(as.character(learning$fribbleID), 1, 1)==3,]$category <- 3

(nrow(learning[learning$category==1,]) / length(unique(learning$subjID))) / 2
```

```
## [1] 20
```

```
(nrow(learning[learning$category==2,]) / length(unique(learning$subjID))) / 2
```

```
## [1] 20
```

```
(nrow(learning[learning$category==3,]) / length(unique(learning$subjID))) / 2
```

```
## [1] 20
```

We have 15 high frequency and 5 low frequency exemplars x category:

```
learning$frequency <- 25
learning[substr(as.character(learning$fribbleID), 4, 5)==75,]$frequency <- 75

(nrow(learning[learning$frequency==25,]) / length(unique(learning$subjID))) / 2
```

```
## [1] 15
```

```
(nrow(learning[learning$frequency==75,]) / length(unique(learning$subjID))) / 2
```

```
## [1] 45
```

Now let's check the fribble-label association:

```
table(learning$category, learning$label, learning$frequency)
```

```
## , ,  = 25
##
##
##     FLbim FLdep FLtob LFbim LFdep LFtob
##   1     0   410     0     0   390     0
##   2   410     0     0   390     0     0
##   3     0     0   410     0     0   390
##
## , ,  = 75
##
##
##     FLbim FLdep FLtob LFbim LFdep LFtob
##   1     0  1230     0     0  1170     0
##   2  1230     0     0  1170     0     0
##   3     0     0  1230     0     0  1170
```

Okay, each label was associated to its correct fribble (coded here as category).

## Check Testing

I'm going to select the tests and clean the rows from Gorilla's http address:

```
tests <- c("generalizationPL", "generalizationLP", "contingencyJudgement", "randomDot");

testing <- raw_data %>%
  filter(task %in% tests)


testing <- droplevels(testing);
rm(tests);

as.factor(gsub("/task/70033/56/asset/|/task/70033/57/asset/", "", testing$fribbleID))-> testing$fribble
as.factor(gsub(".jpg$", "", testing$fribbleID))-> testing$fribbleID

as.factor(gsub("/task/70033/56/asset/|/task/70033/57/asset/", "", testing$label))-> testing$label
as.factor(gsub(".mp3$", "", testing$label))-> testing$label
```

### Check test 1: Generalization from picture to labels

We filter the rows for this task, and clean both the resp and fribble columns.

```
generalizationPL <- testing %>%
  filter(task == 'generalizationPL')
generalizationPL <- droplevels(generalizationPL);

as.factor(gsub("/task/70033/56/asset/|/task/70033/57/asset/", "", generalizationPL$resp))-> generalizat
as.factor(gsub(".mp3$", "", generalizationPL$resp))-> generalizationPL$resp
as.factor(gsub(".jpg", "", generalizationPL$resp))-> generalizationPL$resp

gsub('[[:punct:]]|"', "", generalizationPL$label)-> generalizationPL$label

as.factor(gsub('mp3', "_", generalizationPL$label))-> generalizationPL$label
```

#### Check how many trials participants

```
generalizationPL %>%
  group_by(subjID) %>%
  count()
```

```
## # A tibble: 80 x 2
## # Groups:   subjID [80]
##     subjID     n
##      <int> <int>
##  1 1414932    24
##  2 1414933    24
```

```
## 3 1414937    24
## 4 1414945    24
## 5 1414957    24
## 6 1415040    24
## 7 1420163    24
## 8 1420165    24
## 9 1420169    24
## 10 1420171    24
## # ... with 70 more rows
```

Great, 24 trials per participant.

**Check whether participants saw a unique fribble:**

```
generalizationPL %>%
  group_by(subjID, fribbleID) %>%
  count() %>%
  filter(n > 1)
```

```
## Warning: Factor `fribbleID` contains implicit NA, consider using
## `forcats::fct_explicit_na`

## # A tibble: 0 x 3
## # Groups:   subjID, fribbleID [1]
## # ... with 3 variables: subjID <int>, fribbleID <fct>, n <int>
```

Great!

Integrate stimuli info. In the file "fribbleSet" I have listed all the fribbles ID and their category, along with their cueIDs and body shape. I'm going to add those columns by merging the test file with the fribbleSet by fribbleID. The rest of the file is left untouched.

```
merge(generalizationPL, fribbleSet, by = 'fribbleID')-> generalizationPL;
generalizationPL$label.y <- NULL;

generalizationPL <- rename(generalizationPL, label = label.x);
```

Let's check the responses they made, just to see if they make sense.

For example, we want the resp column to be one of the labels.

```
generalizationPL %>%
  group_by(subjID, resp) %>%
  count()
```

```
## Warning: Factor `resp` contains implicit NA, consider using
## `forcats::fct_explicit_na`

## Warning: Factor `resp` contains implicit NA, consider using
## `forcats::fct_explicit_na`

## Warning: Factor `resp` contains implicit NA, consider using
## `forcats::fct_explicit_na`
```

```
## # A tibble: 291 x 3
## # Groups:   subjID, resp [291]
##     subjID resp      n
##      <int> <fct> <int>
##  1 1414932 bim       6
##  2 1414932 dep       5
##  3 1414932 tob       9
##  4 1414932 <NA>      4
##  5 1414933 bim       8
##  6 1414933 dep       8
##  7 1414933 tob       8
##  8 1414937 bim       8
##  9 1414937 dep       7
## 10 1414937 tob       8
## # ... with 281 more rows
```

Great, some participant missed some trials (coded as NA), but that's okay.

So far, so good.

#### Check trial/stimuli per category, per frequency, per subject

We have 24 trials per participant, but within those trials we *should* have 8 trials per category, 4 low frequency and 4 high frequency trials.

```
head(table(generalizationPL$subjID, generalizationPL$category, generalizationPL$frequency))
```

```
## , ,  = 25
##
##
##           1 2 3
##   1414932 4 4 4
##   1414933 4 4 4
##   1414937 4 4 4
##   1414945 4 4 4
##   1414957 4 4 4
##   1415040 4 4 4
##
## , ,  = 75
##
##
##           1 2 3
##   1414932 4 4 4
##   1414933 4 4 4
##   1414937 4 4 4
##   1414945 4 4 4
##   1414957 4 4 4
##   1415040 4 4 4
```

Let's check the second task.

## Check test 2: Generalization from label to pictures

```
generalizationLP <- testing %>%
  filter(task == 'generalizationLP')
generalizationLP <- droplevels(generalizationLP)
```

### How many trials per participant?

```
generalizationLP %>%
  group_by(subjID) %>%
  count()
```

```
## # A tibble: 80 x 2
## # Groups:   subjID [80]
##     subjID     n
##      <int> <int>
##  1 1414932    24
##  2 1414933    24
##  3 1414937    24
##  4 1414945    24
##  5 1414957    24
##  6 1415040    24
##  7 1420163    24
##  8 1420165    24
##  9 1420169    24
## 10 1420171    24
## # ... with 70 more rows
```

24 trials, great.

### Check whether participants saw a unique fribble

First let's clean the rows from Gorilla gibberish.

```
as.factor(gsub('[[:punct:]]|"', "", generalizationLP$fribbleID))-> generalizationLP$fribbleID

as.factor(gsub('jpg', "_", generalizationLP$fribbleID))-> generalizationLP$fribbleID

as.factor(gsub("/task/70033/56/asset/|/task/70033/57/asset/", "", generalizationLP$resp))-> generalizati

as.factor(gsub(".jpg", "", generalizationLP$resp))-> generalizationLP$resp
```

Then check for duplicates:

```
substr(as.character(generalizationLP$fribbleID), 1, 5)-> temp
substr(as.character(generalizationLP$fribbleID), 7, 11)-> temp2
substr(as.character(generalizationLP$fribbleID), 13, 17)-> temp3

fribblePresented <- c(temp,temp2,temp3)
```

```r
unique(generalizationLP$subjID)-> subj

duplicatedFribbles <- NA;
for (i in 1:length(subj)){
  substr(as.character(generalizationLP[generalizationLP$subjID==subj[i],]$fribbleID), 1, 5)-> temp
  substr(as.character(generalizationLP[generalizationLP$subjID==subj[i],]$fribbleID), 7, 11)-> temp2
  substr(as.character(generalizationLP[generalizationLP$subjID==subj[i],]$fribbleID), 13, 17)-> temp3
  fribblePresented <- c(temp,temp2,temp3)
  dup <- fribblePresented[duplicated(fribblePresented)] #extract duplicated elements
  print(subj[i])

  if (length(dup)>0){
    print(dup)
  } else {
    print(length(dup))
  }

};
```

```
## [1] 1414937
## [1] 0
## [1] 1414945
## [1] 0
## [1] 1414957
## [1] 0
## [1] 1415040
## [1] 0
## [1] 1431949
## [1] 0
## [1] 1431944
## [1] 0
## [1] 1431953
## [1] 0
## [1] 1431958
## [1] 0
## [1] 1431965
## [1] 0
## [1] 1431946
## [1] 0
## [1] 1431957
## [1] 0
## [1] 1431961
## [1] 0
## [1] 1431969
## [1] 0
## [1] 1431978
## [1] 0
## [1] 1431979
## [1] 0
## [1] 1422477
## [1] 0
## [1] 1422675
## [1] 0
```

```
## [1] 1422677
## [1] 0
## [1] 1422679
## [1] 0
## [1] 1422689
## [1] 0
## [1] 1422716
## [1] 0
## [1] 1431972
## [1] 0
## [1] 1431974
## [1] 0
## [1] 1431984
## [1] 0
## [1] 1431992
## [1] 0
## [1] 1431997
## [1] 0
## [1] 1432009
## [1] 0
## [1] 1432011
## [1] 0
## [1] 1432052
## [1] 0
## [1] 1432075
## [1] 0
## [1] 1420163
## [1] 0
## [1] 1420165
## [1] 0
## [1] 1420177
## [1] 0
## [1] 1420180
## [1] 0
## [1] 1420199
## [1] 0
## [1] 1420580
## [1] 0
## [1] 1420622
## [1] 0
## [1] 1422463
## [1] 0
## [1] 1422465
## [1] 0
## [1] 1422466
## [1] 0
## [1] 1422472
## [1] 0
## [1] 1414933
## [1] 0
## [1] 1414932
## [1] 0
## [1] 1420169
## [1] 0
```

```
## [1] 1420171
## [1] 0
## [1] 1420577
## [1] 0
## [1] 1422467
## [1] 0
## [1] 1422475
## [1] 0
## [1] 1422678
## [1] 0
## [1] 1422680
## [1] 0
## [1] 1422681
## [1] 0
## [1] 1431942
## [1] 0
## [1] 1431948
## [1] 0
## [1] 1431966
## [1] 0
## [1] 1431968
## [1] 0
## [1] 1431952
## [1] 0
## [1] 1431954
## [1] 0
## [1] 1431956
## [1] 0
## [1] 1431959
## [1] 0
## [1] 1431960
## [1] 0
## [1] 1431963
## [1] 0
## [1] 1431970
## [1] 0
## [1] 1431981
## [1] 0
## [1] 1431989
## [1] 0
## [1] 1431998
## [1] 0
## [1] 1431999
## [1] 0
## [1] 1432003
## [1] 0
## [1] 1432007
## [1] 0
## [1] 1432030
## [1] 0
## [1] 1420185
## [1] 0
## [1] 1420204
## [1] 0
```

```
## [1] 1420552
## [1] 0
## [1] 1420573
## [1] 0
## [1] 1422470
## [1] 0
## [1] 1422473
## [1] 0
## [1] 1422476
## [1] 0
## [1] 1422676
## [1] 0
## [1] 1422715
## [1] 0
## [1] 1432301
## [1] 0
## [1] 1432323
## [1] 0
```

```r
rm(subj, temp, temp2, temp3, i, fribblePresented, duplicatedFribbles, dup)
```

Great! participants saw always different fribble.

#### Check whether fribbles presented were either high or low frequency within trials

In this task we have three pictures and one label pronounced. This means that the fribbleID column contains 3 images. I'm going to cycle over the dataset, and break the fribbleID column in three, then I'm going to print the fribble that within the same trial has a different frequency. I'm going to print the fribbles that are presented wrongly, e.g., "low high low" etc. If all fribbles are presented correctly: , e.g., "low low low" and "high high high", then the output is empty.

```r
unique(generalizationLP$subjID)-> subj;

trials <- NULL;
task <- NULL;

for (i in 1:length(subj)){
  as.integer(substr(as.character(generalizationLP[generalizationLP$subjID==subj[i],]$fribbleID), 4, 5))
  as.integer(substr(as.character(generalizationLP[generalizationLP$subjID==subj[i],]$fribbleID), 10, 11
  as.integer(substr(as.character(generalizationLP[generalizationLP$subjID==subj[i],]$fribbleID), 16, 17
trials <- cbind(temp, temp2, temp3, as.integer(subj[i])) # store it in columns along with subj info
task <- rbind(task, trials) #store all subjs
};

for (i in 1:nrow(task)){ #check by rows whether there is a unique number, print the row if wrong
  if ((task[i,1] == task[i,2] & task[i,3])== FALSE) {
    print('wrong frequency fribble:')
    print(task[i,1], task[i,2], task[i,3])
  }
};

frequency <- ifelse(substr(as.character(task[,1]), 1, 1)==2, 'low', 'high')
cbind(task, frequency)->task
```

```r
as.data.frame(task)-> task
rm(trials, i, subj, temp, temp2, temp3);
```

Great, fribbles presented were either low or high frequency. Check whether participants saw 4 trials with low and 4 trials with high frequency:

**Check trial distribution per frequency:**

```r
head(table(task$V4, task$frequency))
```

```
##
##            high low
##   1414932    12  12
##   1414933    12  12
##   1414937    12  12
##   1414945    12  12
##   1414957    12  12
##   1415040    12  12
```

I'm going to merge the stimuli set now.

When we do it, this time we need to merge by resp and not by fribbleID, because our fribble selected is coded in this column:

```r
fribbleSet$resp <- fribbleSet$fribbleID # column's name needs to be the same in order to merge
merge(generalizationLP, fribbleSet, by = 'resp', all.x = T)-> generalizationLP;
fribbleSet$resp <- NULL;
generalizationLP$fribbleID.y <- NULL;
generalizationLP$label.y <- NULL;
generalizationLP <- rename(generalizationLP, label = label.x);
generalizationLP <- rename(generalizationLP, fribbleID = fribbleID.x);
```

**Check responses distribution by category:**

```r
generalizationLP %>%
  group_by(subjID, category) %>%
  count()
```

```
## # A tibble: 295 x 3
## # Groups:   subjID, category [295]
##     subjID category     n
##      <int>    <int> <int>
##   1 1414932        1     7
##   2 1414932        2    11
##   3 1414932        3     2
##   4 1414932       NA     4
##   5 1414933        1     8
##   6 1414933        2     5
```

```
##  7 1414933        3    10
##  8 1414933       NA     1
##  9 1414937        1     7
## 10 1414937        2     7
## # ... with 285 more rows
```

Cool.

**Check responses distribution by frequency:**

```
generalizationLP %>%
  group_by(subjID, label, frequency) %>%
  count()
```

```
## # A tibble: 583 x 4
## # Groups:   subjID, label, frequency [583]
##     subjID label frequency     n
##      <int> <fct>     <int> <int>
##  1 1414932 bim          25     3
##  2 1414932 bim          75     4
##  3 1414932 bim          NA     1
##  4 1414932 dep          25     3
##  5 1414932 dep          75     3
##  6 1414932 dep          NA     2
##  7 1414932 tob          25     3
##  8 1414932 tob          75     4
##  9 1414932 tob          NA     1
## 10 1414933 bim          25     4
## # ... with 573 more rows
```

## Check test 3: Contingency Judgement task

```
contingencyJudgement <- testing %>%
  filter(task == 'contingencyJudgement')
contingencyJudgement <- droplevels(contingencyJudgement)
```

**How many trials per participant?**

```
contingencyJudgement %>%
  group_by(subjID) %>%
  count()
```

```
## # A tibble: 80 x 2
## # Groups:   subjID [80]
##     subjID     n
##      <int> <int>
##  1 1414932    24
```

```
##   2 1414933    24
##   3 1414937    24
##   4 1414945    24
##   5 1414957    24
##   6 1415040    24
##   7 1420163    24
##   8 1420165    24
##   9 1420169    24
## 10 1420171    24
## # ... with 70 more rows
```

Very good.

#### Did participants see a fribble more than once?

```
droplevels(contingencyJudgement) %>%
  group_by(subjID, fribbleID) %>%
  count() %>%
  filter( n > 1)
```

```
## Warning: Factor `fribbleID` contains implicit NA, consider using
## `forcats::fct_explicit_na`
```

```
## # A tibble: 0 x 3
## # Groups:   subjID, fribbleID [1]
## # ... with 3 variables: subjID <int>, fribbleID <fct>, n <int>
```

No! that's great.

#### Are labels repeated equally?

```
table(contingencyJudgement$subjID, contingencyJudgement$label)
```

```
##
##            bim dep tob
##    1414932   8   8   8
##    1414933   8   8   8
##    1414937   8   8   8
##    1414945   8   8   8
##    1414957   8   8   8
##    1415040   8   8   8
##    1420163   8   8   8
##    1420165   8   8   8
##    1420169   8   8   8
##    1420171   8   8   8
##    1420177   8   8   8
##    1420180   8   8   8
##    1420185   8   8   8
##    1420199   8   8   8
```

```
##     1420204    8    8    8
##     1420552    8    8    8
##     1420573    8    8    8
##     1420577    8    8    8
##     1420580    8    8    8
##     1420622    8    8    8
##     1422463    8    8    8
##     1422465    8    8    8
##     1422466    8    8    8
##     1422467    8    8    8
##     1422470    8    8    8
##     1422472    8    8    8
##     1422473    8    8    8
##     1422475    8    8    8
##     1422476    8    8    8
##     1422477    8    8    8
##     1422675    8    8    8
##     1422676    8    8    8
##     1422677    8    8    8
##     1422678    8    8    8
##     1422679    8    8    8
##     1422680    8    8    8
##     1422681    8    8    8
##     1422689    8    8    8
##     1422715    8    8    8
##     1422716    8    8    8
##     1431942    8    8    8
##     1431944    8    8    8
##     1431946    8    8    8
##     1431948    8    8    8
##     1431949    8    8    8
##     1431952    8    8    8
##     1431953    8    8    8
##     1431954    8    8    8
##     1431956    8    8    8
##     1431957    8    8    8
##     1431958    8    8    8
##     1431959    8    8    8
##     1431960    8    8    8
##     1431961    8    8    8
##     1431963    8    8    8
##     1431965    8    8    8
##     1431966    8    8    8
##     1431968    8    8    8
##     1431969    8    8    8
##     1431970    8    8    8
##     1431972    8    8    8
##     1431974    8    8    8
##     1431978    8    8    8
##     1431979    8    8    8
##     1431981    8    8    8
##     1431984    8    8    8
##     1431989    8    8    8
##     1431992    8    8    8
```

```
##   1431997   8   8   8
##   1431998   8   8   8
##   1431999   8   8   8
##   1432003   8   8   8
##   1432007   8   8   8
##   1432009   8   8   8
##   1432011   8   8   8
##   1432030   8   8   8
##   1432052   8   8   8
##   1432075   8   8   8
##   1432301   8   8   8
##   1432323   8   8   8
```

good

```
merge(contingencyJudgement, fribbleSet, by = 'fribbleID')-> contingencyJudgement
contingencyJudgement$label.y <- NULL;
contingencyJudgement <- rename(contingencyJudgement, label = label.x)
```

**Check category presentation:**

```
contingencyJudgement %>%
  group_by(subjID, category) %>%
  count()
```

```
## # A tibble: 240 x 3
## # Groups:   subjID, category [240]
##     subjID category     n
##      <int>    <int> <int>
##  1 1414932        1     8
##  2 1414932        2     8
##  3 1414932        3     8
##  4 1414933        1     8
##  5 1414933        2     8
##  6 1414933        3     8
##  7 1414937        1     8
##  8 1414937        2     8
##  9 1414937        3     8
## 10 1414945        1     8
## # ... with 230 more rows
```

## Check test 4: Random dot task

Let's check our random dot task. This was inserted randomly during trials 4 times. 5 trials each time, plus 4 practice trials.

```
randomDot <- testing %>%
  filter(task == 'randomDot')
```

### How many trials per participant?

```
randomDot %>%
  group_by(subjID) %>%
  count()
```

```
## # A tibble: 80 x 2
## # Groups:   subjID [80]
##     subjID     n
##      <int> <int>
##  1 1414932    26
##  2 1414933    26
##  3 1414937    26
##  4 1414945    26
##  5 1414957    26
##  6 1415040    26
##  7 1420163    26
##  8 1420165    26
##  9 1420169    26
## 10 1420171    26
## # ... with 70 more rows
```

we have 5 trials repeated during learning four times (20) plus 4 practice trials.

### How was accuracy distributed across participants?

First, let's consider that when we have a timeout, the output is -1

```
randomDot %>%
  group_by(subjID, resp) %>%
  filter(rt == -1) %>%
  count()
```

```
## # A tibble: 57 x 3
## # Groups:   subjID, resp [57]
##     subjID resp      n
##      <int> <fct> <int>
##  1 1414932 -1       10
##  2 1414933 -1        1
##  3 1414945 -1        3
##  4 1415040 -1        1
##  5 1420163 -1        2
##  6 1420165 -1        1
##  7 1420180 -1        2
##  8 1420185 -1        1
##  9 1420204 -1        1
## 10 1420552 -1        3
## # ... with 47 more rows
```

Here we can see that some participant missed some trials.

Let's see how accuracy is coded when response is -1:

```r
head(randomDot[randomDot$rt == -1,]$acc)
```

```
## [1] NA NA NA NA NA NA
```

So it is coded as "NA", great. However:

```r
nrow(randomDot[is.na(randomDot$acc),]) #total of NA
```

```
## [1] 198
```

```r
nrow(randomDot[randomDot$resp == -1,]) # total of timeouts
```

```
## [1] 127
```

There are more NA's in acc than can be explained by timeouts. This means that also wrong responses are coded as NA. We need to recode those.

```r
randomDot[is.na(randomDot$acc),]$acc <- 0 #recode everything that is wrong or timeout as 0
```

**Check the overall accuracy of participants, filtering by timeouts:**

```r
aggregate(acc ~ subjID, data = randomDot[!(randomDot$resp == -1),], FUN = mean)# without timeouts
```

```
##     subjID       acc
## 1  1414932 0.6875000
## 2  1414933 1.0000000
## 3  1414937 1.0000000
## 4  1414945 1.0000000
## 5  1414957 1.0000000
## 6  1415040 1.0000000
## 7  1420163 0.9583333
## 8  1420165 0.9600000
## 9  1420169 1.0000000
## 10 1420171 1.0000000
## 11 1420177 1.0000000
## 12 1420180 0.9583333
## 13 1420185 1.0000000
## 14 1420199 1.0000000
## 15 1420204 1.0000000
## 16 1420552 1.0000000
## 17 1420573 1.0000000
## 18 1420577 0.9583333
## 19 1420580 1.0000000
## 20 1420622 1.0000000
## 21 1422463 1.0000000
## 22 1422465 1.0000000
## 23 1422466 0.9565217
## 24 1422467 1.0000000
```

```
## 25 1422470 0.7600000
## 26 1422472 1.0000000
## 27 1422473 1.0000000
## 28 1422475 0.5200000
## 29 1422476 0.9600000
## 30 1422477 1.0000000
## 31 1422675 1.0000000
## 32 1422676 0.9615385
## 33 1422677 0.9047619
## 34 1422678 0.9600000
## 35 1422679 0.9565217
## 36 1422680 1.0000000
## 37 1422681 1.0000000
## 38 1422689 0.6000000
## 39 1422715 1.0000000
## 40 1422716 1.0000000
## 41 1431942 0.8461538
## 42 1431944 0.7619048
## 43 1431946 1.0000000
## 44 1431948 0.9600000
## 45 1431949 1.0000000
## 46 1431952 0.9565217
## 47 1431953 0.9615385
## 48 1431954 1.0000000
## 49 1431956 0.9166667
## 50 1431957 1.0000000
## 51 1431958 0.9615385
## 52 1431959 1.0000000
## 53 1431960 1.0000000
## 54 1431961 1.0000000
## 55 1431963 1.0000000
## 56 1431965 1.0000000
## 57 1431966 0.9600000
## 58 1431968 1.0000000
## 59 1431969 1.0000000
## 60 1431970 0.9565217
## 61 1431972 0.9600000
## 62 1431974 1.0000000
## 63 1431978 1.0000000
## 64 1431979 1.0000000
## 65 1431981 1.0000000
## 66 1431984 0.9600000
## 67 1431989 1.0000000
## 68 1431992 1.0000000
## 69 1431997 1.0000000
## 70 1431998 1.0000000
## 71 1431999 1.0000000
## 72 1432003 0.9130435
## 73 1432007 1.0000000
## 74 1432009 0.9600000
## 75 1432011 0.9090909
## 76 1432030 1.0000000
## 77 1432052 0.9166667
## 78 1432075 0.9600000
```

```
## 79 1432301 1.0000000
## 80 1432323 1.0000000
```

Now that we have all tests separated, better to remove this file:

# Data visualization

Okay, from the sanity checks done above we can draw two conclusions:

1. Learning and Testing was presented as it was supposed to be and
2. data was stored correctly

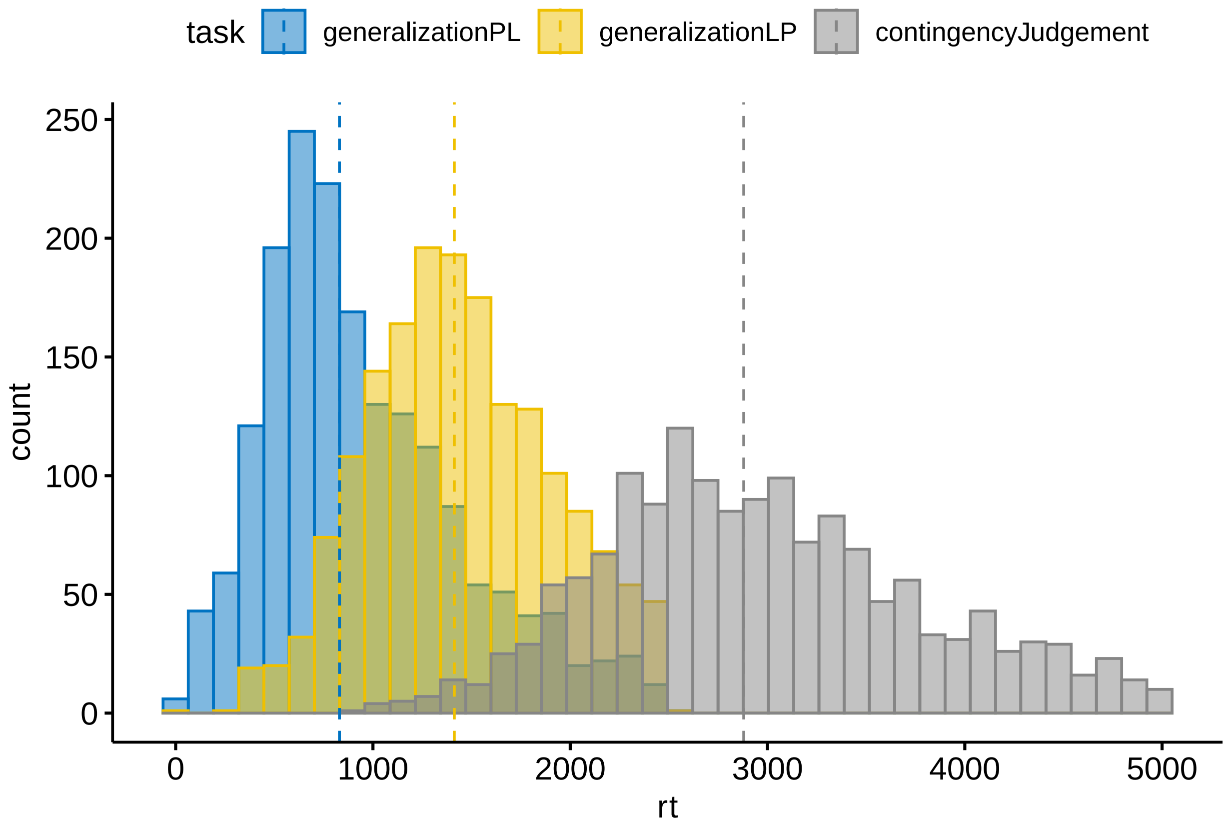
Let's see now if data makes sense.

## Reaction times

```
rbind(generalizationPL, generalizationLP, contingencyJudgement)-> alltasks
alltasks <- droplevels(alltasks)
```

```
gghistogram(alltasks,
       x = "rt",
       y = "..count..",
       xlab = "rt",
       color = "task",
       fill = "task",
       bins = 40,
       palette = "jco",
       add = "median"
)
```

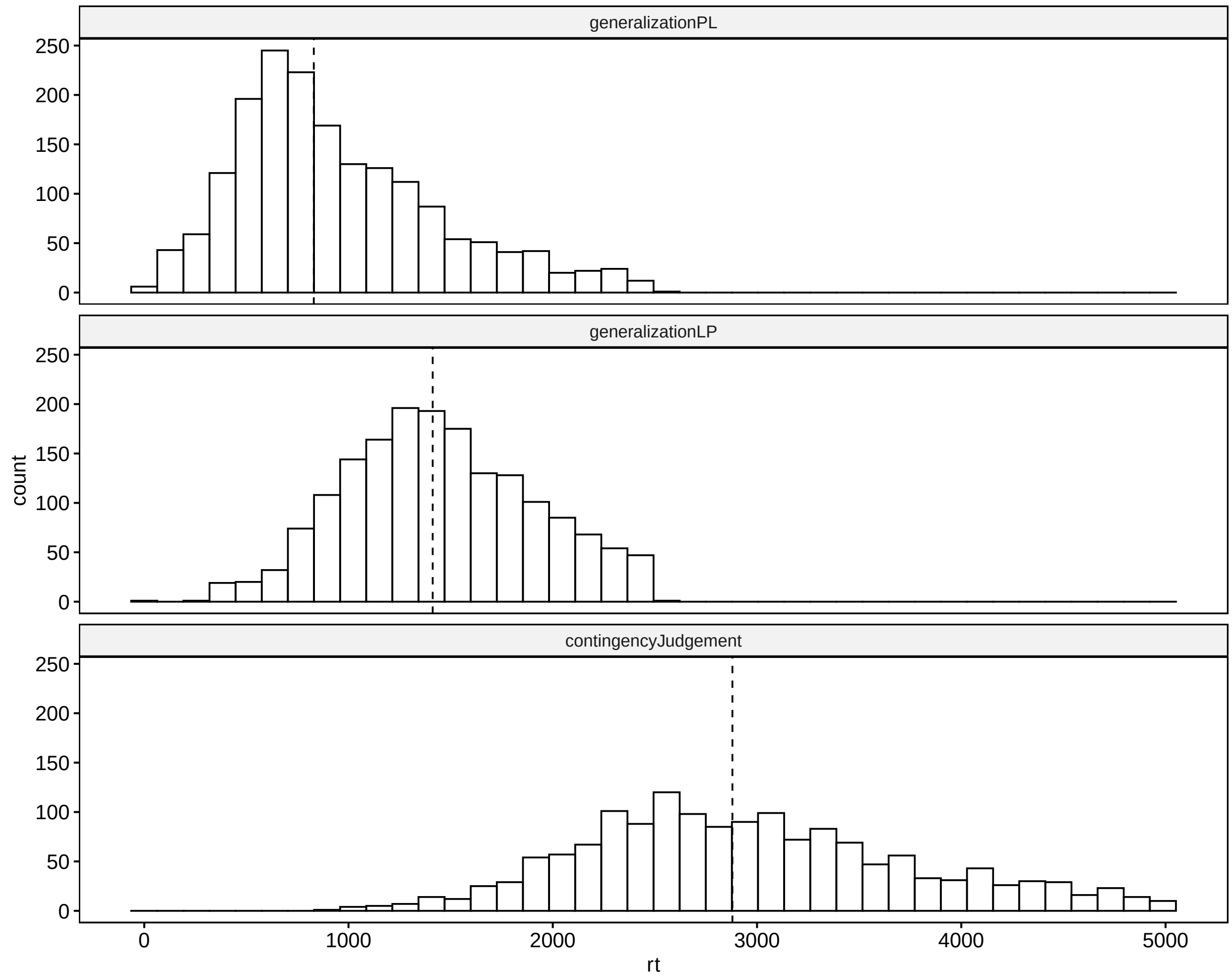
```
## Warning: Removed 697 rows containing non-finite values (stat_bin).
```




The two generalization tasks looks quite different. I'm going to plot it separately for a better inspection:

```
p<- gghistogram(alltasks, #will throw warnings related to non responses but that's okay, ggplot simply
        x = "rt",
        y = "..count..",
        xlab = "rt",
        facet.by = "task",
        add = "median",
        bins = 40
)

facet(p, facet.by = "task",
      nrow = 3,
      ncol = 1)
```

```
## Warning: Removed 697 rows containing non-finite values (stat_bin).
```




The tails of the first two tasks don't end smoothly, especially in task 2.

## accuracy

### RandomDot

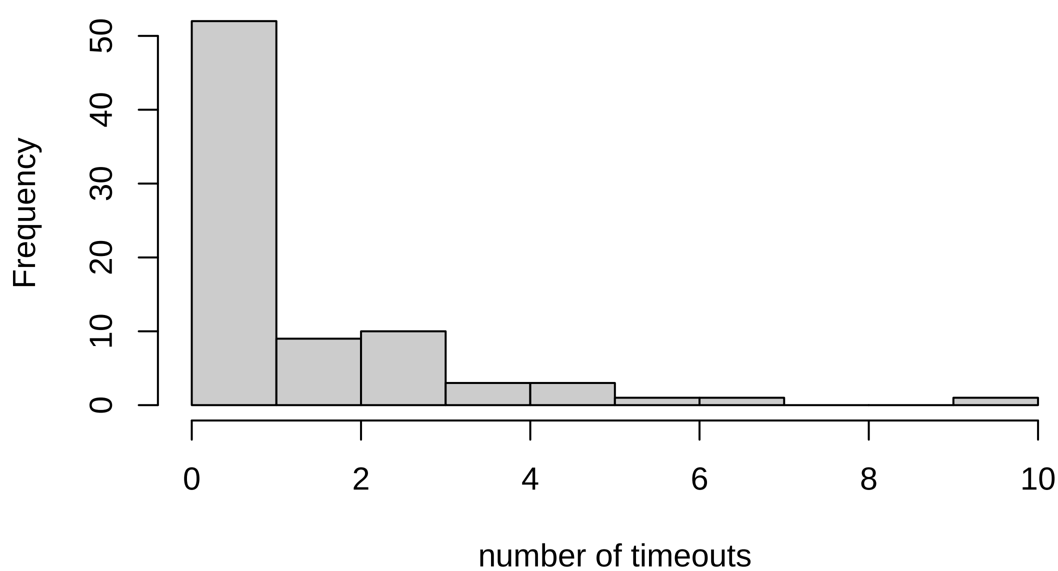
```
unique(randomDot$subjID)-> subj;
randomDot-> randomTask

trials <- c(rep('0', 6), rep('1', 5),
              rep('2', 5), rep('3', 5),
              rep('4', 5))

trialstot <- as.factor(rep(trials, length(subj)))

randomTask$blocks <- trialstot
```

```
randomTask$timeout <- ifelse(randomTask$resp== -1, 1, 0)
```

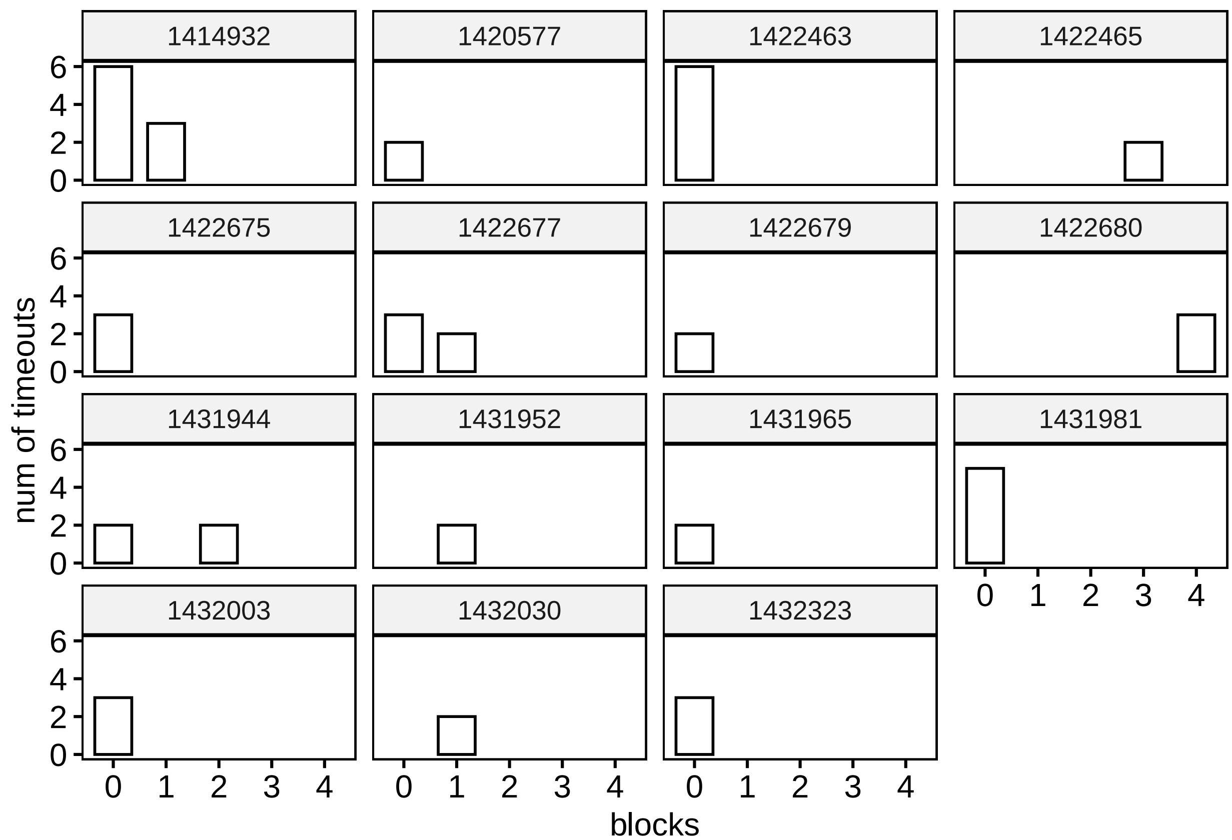
```
temp<-randomTask %>%
  count(timeout, subjID) %>%
  filter(timeout == 1)

unique(temp$subjID)-> subjs

temp2<-randomTask[!(randomTask$subjID %in% subjs),] %>%
  count(timeout, subjID) %>%
  filter(timeout == 0)

temp2[temp2$timeout==0,]$n <- 0

rbind(temp,temp2)-> timeout
```

**How many timeouts by participant?** Histrogram by participant:

```
hist(timeout$n, xlab = 'number of timeouts',
     main = '',
     col=grey(.80),
     border=grey(0),
     breaks = seq(0,max(timeout$n),1))
```



```r
timeout <- randomTask %>%
  group_by(subjID, blocks) %>%
  filter(resp == -1) %>%
  count()


ggbarplot(timeout[timeout$n>1,], x = "blocks", y = "n",
          facet.by = "subjID",
          sort.by.groups = TRUE,      # Sort inside each group
          ylab = "num of timeouts")
```



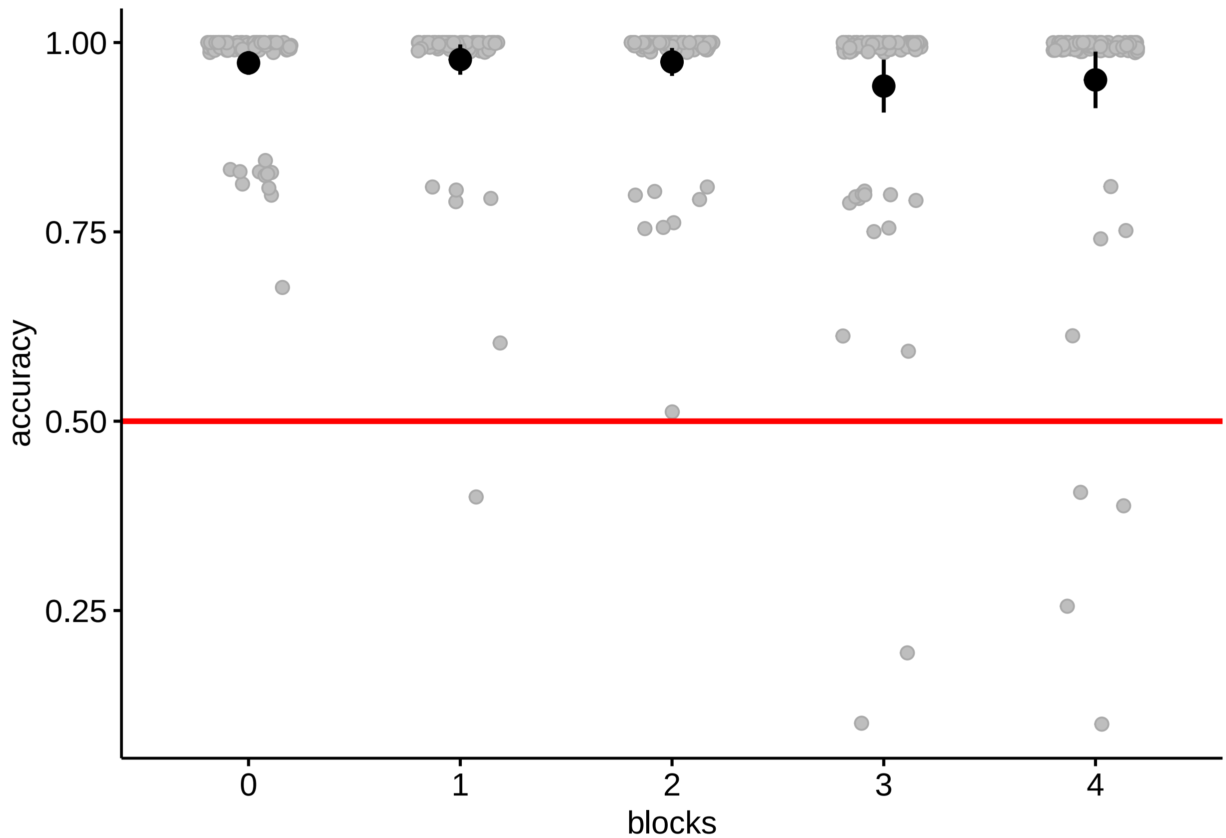

#### Subjects that made more than 3 timeouts

```r
unique(timeout[timeout$n>3,]$subjID) -> problematicPeople
```

```r
accdistr <- randomTask[!(randomTask$resp == -1),] %>%
  group_by(subjID, blocks) %>%
  summarise(m = mean(acc))
```

```r
ggstripchart(accdistr, x = "blocks", y = "m",
             xlab = "blocks",
             ylab = "accuracy",
             add = "mean_ci",
             size = 2,
             color = "darkgray",
```

```
             shape = 21,
             fill = "gray",
             error.plot = "pointrange",
             add.params = list(color = "black",
                               size = 0.7)) +
  scale_y_continuous(limits = c(0.1, 1), oob = scales::squish) + #to prevent jitter to move above 100%
  geom_hline(yintercept = .50, col='red', lwd=1);
```




```
accdistr[accdistr$m<=.5,]
```

```
## # A tibble: 8 x 3
## # Groups:   subjID [5]
##    subjID blocks     m
##     <int> <fct>  <dbl>
## 1 1414932 4       0.25
## 2 1422470 1       0.4
## 3 1422475 2       0.5
## 4 1422475 3       0.2
## 5 1422475 4       0
## 6 1422689 3       0
## 7 1422689 4       0.4
## 8 1431942 4       0.4
```

```r
c("1422475", "1422689") -> dumbPeople
```

```r
setdiff(dumbPeople, problematicPeople)-> dumbPeople
```

**People that scored less than 50% in >1 block:** Let's consider them as bad subjects.

```r
c(problematicPeople, dumbPeople)->badsubjs
```

```r
rm(temp, temp2, timeout, subj, subjs, trials, trialstot, accdistr)
```

### Task 1: from picture to labels

The column fribbleID stores the fribble presented, while the column label stores the labels presented. Resp column in this task refers to the label selected. Category and frequency refers to the fribbleID column.

I'm going to add 1 in the accuracy column for every instance where response matches the category column, i.e., the participant correctly associated the fribble to its label.

I remove the no-response, and compute accuracy based on category and response.

```r
length(unique(generalizationPL$subjID))
```

**How many participants do we have per learning?**

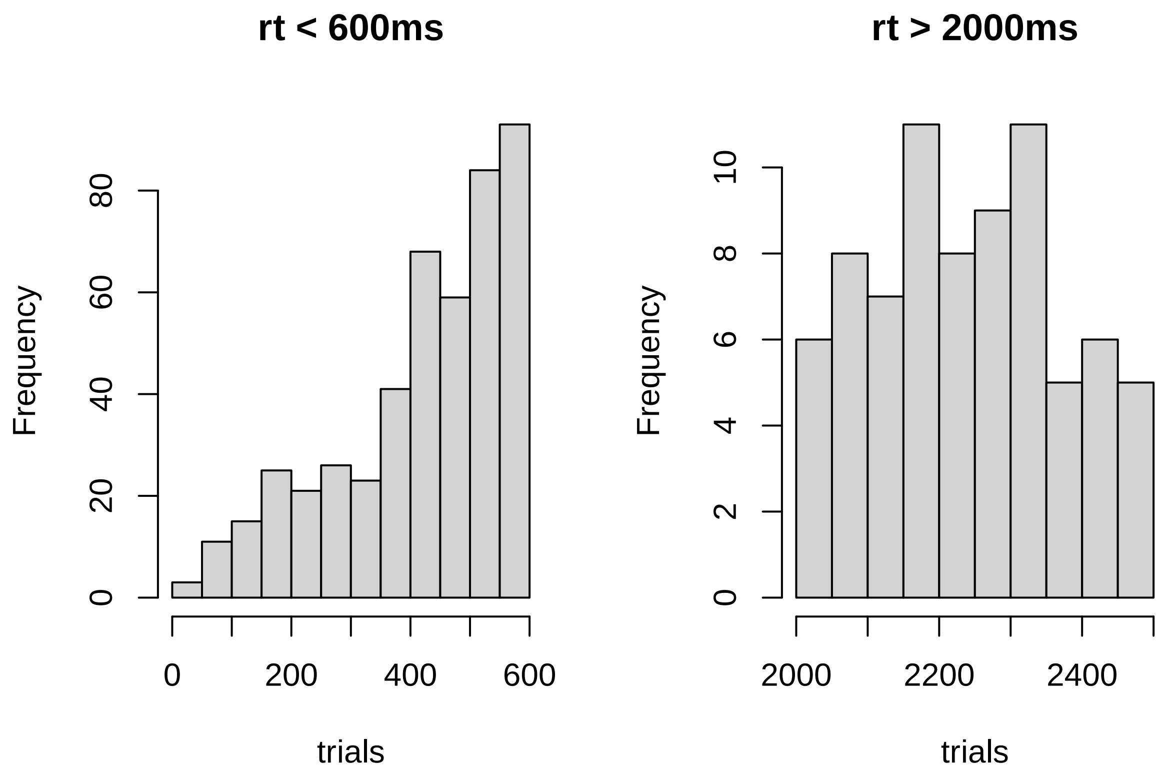
```
## [1] 80
```

```r
fl<- length(unique(generalizationPL[generalizationPL$learning=='FL',]$subjID))
lf<- length(unique(generalizationPL[generalizationPL$learning=='LF',]$subjID))
```

We have 41 for feature-label learning, and 39 for label-feature learning.

**Check tails of the rt distribution** The point is that we can't rely on responses made very early, because these might be simply mistakes or technical errors.

```r
par(mfrow=c(1,2))
hist(generalizationPL[generalizationPL$rt<600,]$rt, main = 'rt < 600ms', xlab = 'trials');
hist(generalizationPL[generalizationPL$rt>2000,]$rt, main = 'rt > 2000ms', xlab = 'trials');
```




```r
par(mfrow=c(1,1))
```

I would remove rt <100ms for all tasks.

```r
round(nrow(generalizationPL[generalizationPL$rt<100,]) / nrow(generalizationPL)*100,2)
```

**How many, what type of trials do we have?**

```
## [1] 7.81
```

```r
rm(fl,lf)
pictureLabel <- generalizationPL[!(is.na(generalizationPL$resp)),]

pictureLabel$acc <- 0;
pictureLabel[pictureLabel$category==1 & pictureLabel$resp=='dep',]$acc <- 1;

pictureLabel[pictureLabel$category==2 & pictureLabel$resp=='bim',]$acc <- 1;

pictureLabel[pictureLabel$category==3 & pictureLabel$resp=='tob',]$acc <- 1;
```

```r
n <- length(unique(pictureLabel$subjID))
nrows <- (nrow(generalizationPL)) - (nrow(pictureLabel))
```

```r
sort(unique(pictureLabel$subjID))-> subjs;
sort(unique(generalizationPL$subjID)) ->totsubjs;

subjmissed<- setdiff(totsubjs, subjs);

rm(subjs, totsubjs);
```

We have 79 participants in this task, this is -1 compared to our total number of participants. The subject(s) that didn't answer at all the task is: 1420171. We have lost also 136 responses, that is 7.0833333 over the total: 1920.

How many trials per participant do we have now?

```r
pictureLabel %>%
  group_by(subjID) %>%
  count()
```

```
## # A tibble: 79 x 2
## # Groups:   subjID [79]
##     subjID     n
##      <int> <int>
##  1 1414932    20
##  2 1414933    24
##  3 1414937    23
##  4 1414945    20
##  5 1414957    23
##  6 1415040    23
##  7 1420163    23
##  8 1420165    21
##  9 1420169    24
## 10 1420177    23
## # ... with 69 more rows
```

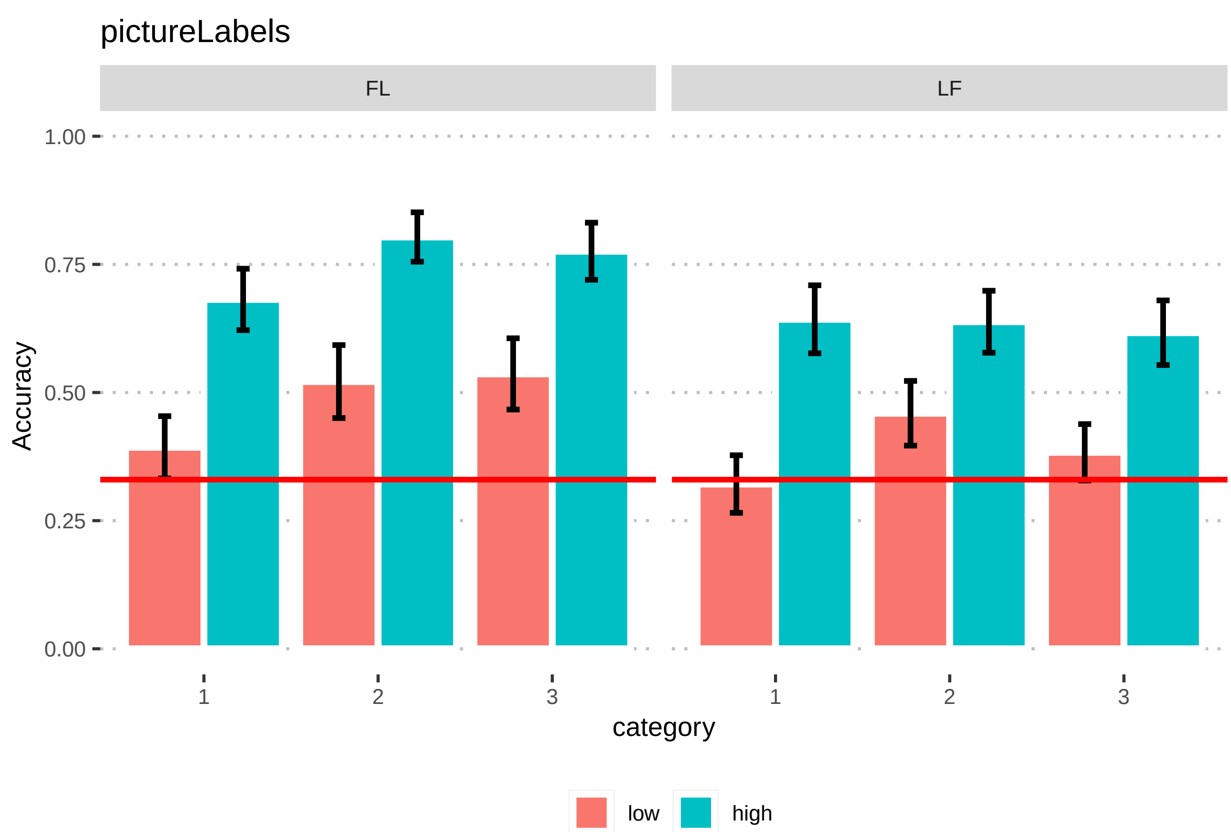
No one had less than 18 trials, over the total (24). That's fine!

**Barplot accuracy by category + frequency + learning**   picture label

```r
c(badsubjs, subjmissed) -> badsubjs

rm(n, subjmissed, nrows)

ss_prop<-aggregate(acc ~ frequency+category+subjID+learning,
                   data = pictureLabel[pictureLabel$rt > 100 &
                                         !(pictureLabel$subjID %in% badsubjs),], FUN = mean)
```

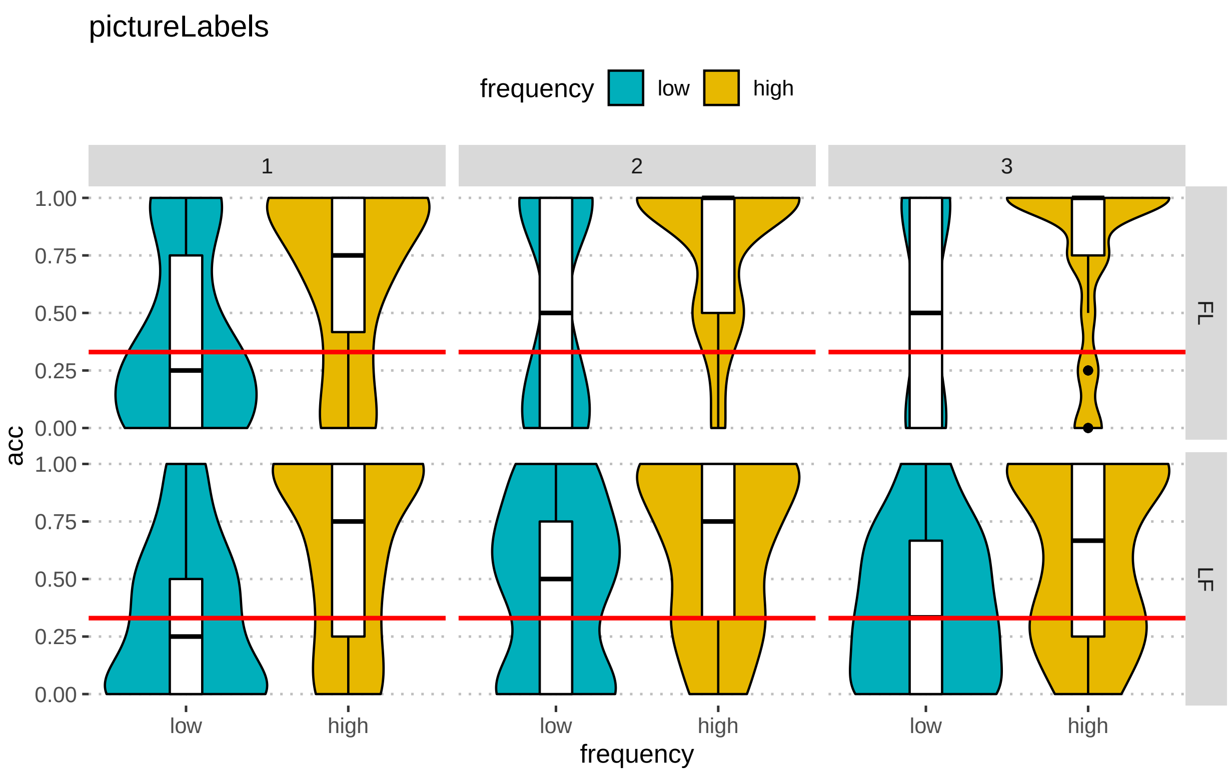
Plot aggregated over subjs. To see accuracy distributed over categories.

```r
ms <- ss_prop %>%
  group_by( category, frequency, learning) %>%
  summarise(n=n(),
    mean=mean(acc),
    sd=sd(acc)
  ) %>%
  mutate( se=sd/sqrt(n))  %>%
  mutate( ci=se * qt((1-0.05)/2 + .5, n-1))

ms$frequency <- as.factor(ms$frequency)
plyr::revalue(ms$frequency, c("25"="low"))-> ms$frequency;
plyr::revalue(ms$frequency, c("75"="high"))-> ms$frequency;

ggplot(aes(x = category, y = mean, fill = frequency), data = ms) +
  facet_grid( . ~ learning) +
  geom_bar(stat = "identity", color='white', position=position_dodge(), size=1.2) +
  geom_errorbar(aes(ymin=mean-se, ymax=mean+se), width=.15, size=1,position=position_dodge(.9)) +
  ylab("Accuracy ") +
  xlab("category") +
  ggtitle('pictureLabels') +
  coord_cartesian(ylim = c(0, 1))+
  ggpubr::theme_pubclean() +
  theme(legend.position="bottom", legend.title = element_blank()) +
  theme(text = element_text(size=10)) +
  geom_hline(yintercept = .33, col='red', lwd=1);
```



```
df <- aggregate(acc ~ subjID+frequency+learning+category,
                data = pictureLabel[pictureLabel$rt > 100  &
                                      !(pictureLabel$subjID %in% badsubjs),], mean)
df$frequency <- as.factor(df$frequency)
plyr::revalue(df$frequency, c("25"="low"))-> df$frequency;
plyr::revalue(df$frequency, c("75"="high"))-> df$frequency;

ggviolin(df, x = "frequency", y = "acc", fill = "frequency",
         palette = c("#00AFBB", "#E7B800"),
         add = "boxplot",
         add.params = list(fill = "white"),
         trim=TRUE) +
        ggtitle('pictureLabels') +
        facet_grid( learning ~ category) +
        theme_pubclean()+
  geom_hline(yintercept = .33, col='red', lwd=1);
```

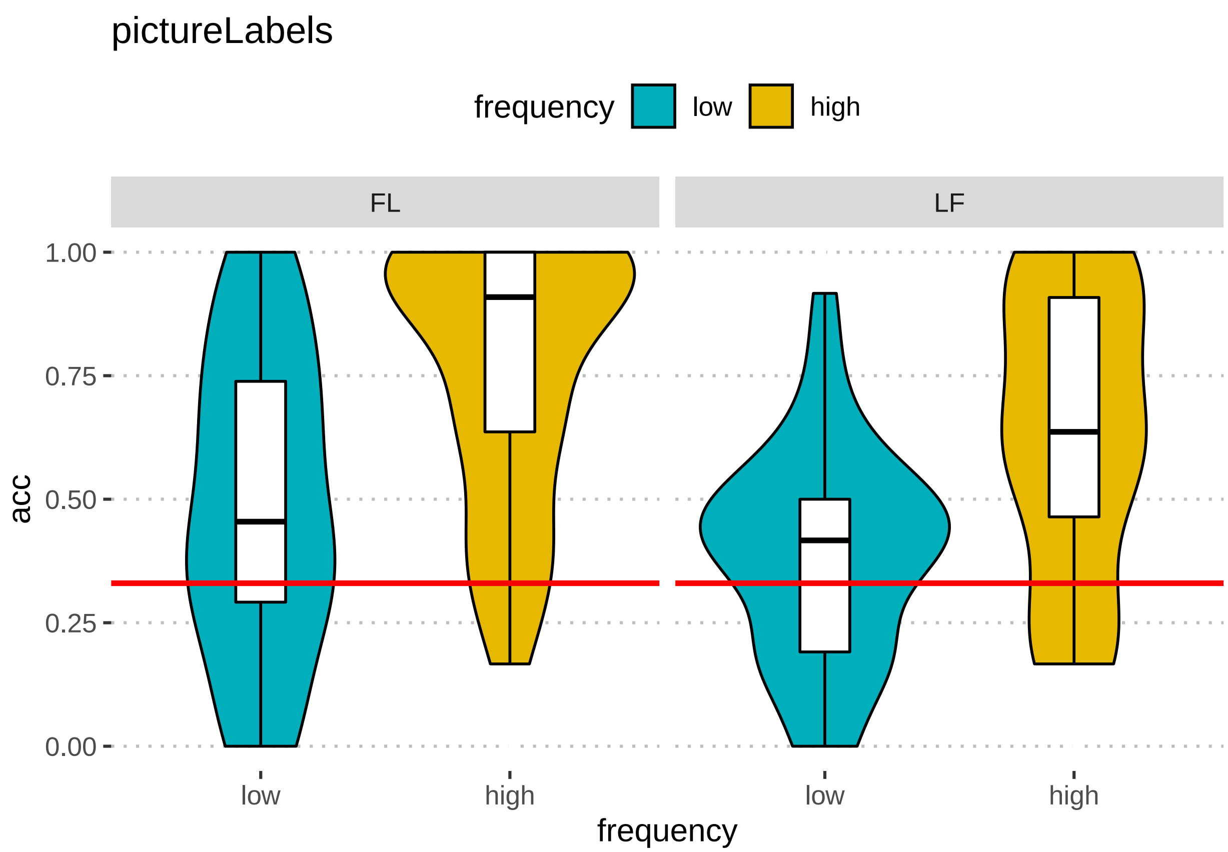
**Violin plot accuracy by category + frequency + learning**




**Violin plot accuracy by frequency + learning** Let's see how participants scored for the high/low frequency:

```
df <- aggregate(acc ~ subjID+frequency+learning,
                data = pictureLabel[pictureLabel$rt > 100  &
                                      !(pictureLabel$subjID %in% badsubjs),], mean)
```

```
df$frequency <- as.factor(df$frequency)
plyr::revalue(df$frequency, c("25"="low"))-> df$frequency;
plyr::revalue(df$frequency, c("75"="high"))-> df$frequency;

ggviolin(df, x = "frequency", y = "acc", fill = "frequency",
         palette = c("#00AFBB", "#E7B800"),
         add = "boxplot",
         add.params = list(fill = "white"),
         trim=TRUE) +
        ggtitle('pictureLabels') +
        facet_grid( . ~ learning) +
        theme_pubclean()+
  geom_hline(yintercept = .33, col='red', lwd=1);
```



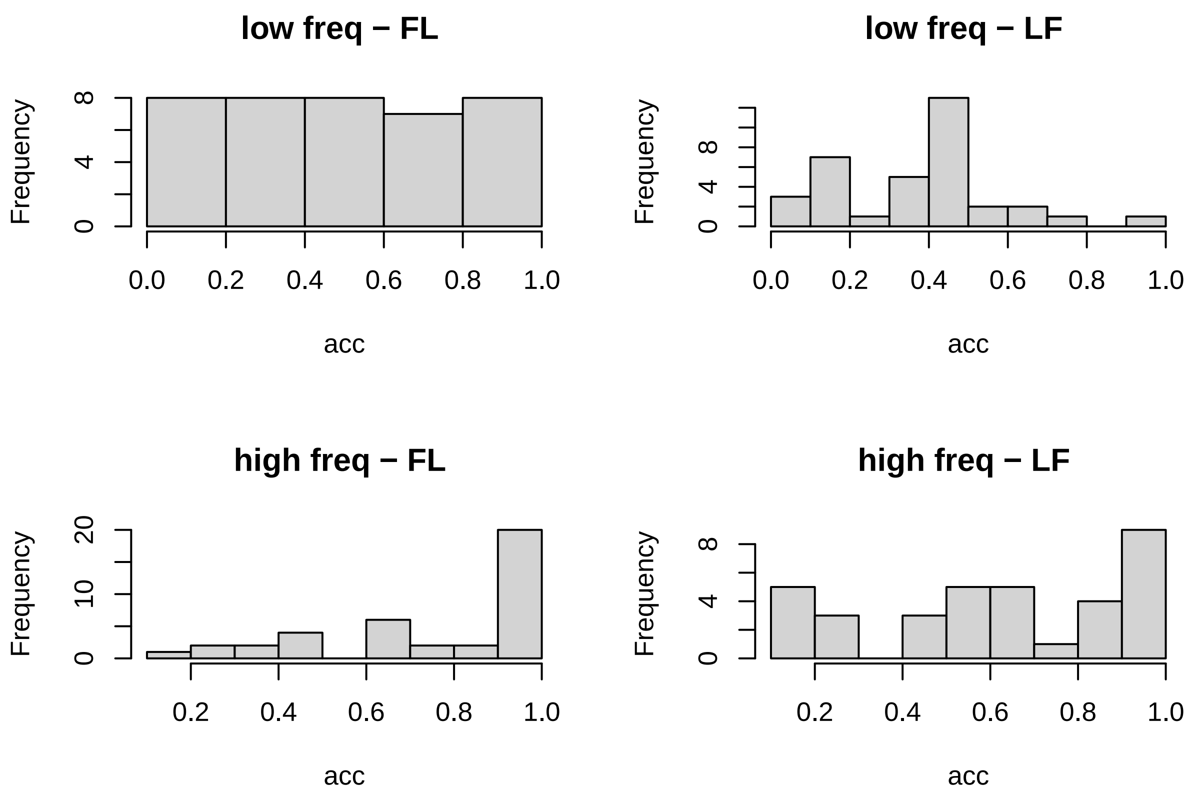

```
df %>%
  group_by(learning, frequency) %>%
  summarise(mean(acc))
```

```
## # A tibble: 4 x 3
## # Groups:   learning [2]
##   learning frequency `mean(acc)`
##   <fct>    <fct>           <dbl>
## 1 FL       low             0.489
## 2 FL       high            0.760
## 3 LF       low             0.386
```

```
## 4 LF        high             0.636
```

Closer inspection:

```
par(mfrow=c(2,2))
hist(df[df$frequency=='low' & df$learning=='FL',]$acc, xlab = 'acc', main = 'low freq - FL ')
hist(df[df$frequency=='low' & df$learning=='LF',]$acc, xlab = 'acc', main = 'low freq - LF ')
hist(df[df$frequency=='high' & df$learning=='FL',]$acc, xlab = 'acc', main = 'high freq - FL ')
hist(df[df$frequency=='high' & df$learning=='LF',]$acc, xlab = 'acc', main = 'high freq - LF ')
```




```
par(mfrow=c(1,1))
```

```


#barPlot aggregated over categories:

ms <- aggregate(acc ~ subjID+frequency+learning,
                data=pictureLabel[pictureLabel$rt > 100 &
                                  !(pictureLabel$subjID %in% badsubjs)   ,], FUN= mean)

df<- ms %>%
  group_by(frequency, learning)%>%
  summarise(
    mean = mean(acc),
```

```
    sd = sd(acc),
    n = n()) %>%
  mutate( se=sd/sqrt(n))  %>%
  mutate( ci=se * qt((1-0.05)/2 + .5, n-1))

df$frequency <- as.factor(df$frequency)
plyr::revalue(df$frequency, c("25"="low"))-> df$frequency;
plyr::revalue(df$frequency, c("75"="high"))-> df$frequency;


pl<-ggplot(aes(x = frequency, y = mean, fill = frequency), data = df) +
  facet_grid( . ~ learning) +
  geom_bar(stat = "identity", color='white', position=position_dodge(), size=1.2) +
  geom_errorbar(aes(ymin=mean-se, ymax=mean+se), width=.15, size=1,position=position_dodge(.9)) +
  ylab("Accuracy ") +
  xlab("frequency") +
  ggtitle('pictureLabels') +
  coord_cartesian(ylim = c(0, 1))+
  ggpubr::theme_pubclean() +
  theme(legend.position="bottom", legend.title = element_blank()) +
  theme(text = element_text(size=10)) +
  geom_hline(yintercept = .33, col='red', lwd=1);
```

**Barplot accuracy by frequency + learning**

### Task 2: from label to pictures

Let's check now the generalizaton from label to pictures:

```
length(unique(generalizationLP$subjID))
```

```
## [1] 80
```

```
fl<- length(unique(generalizationLP[generalizationLP$learning=='FL',]$subjID))
lf<- length(unique(generalizationLP[generalizationLP$learning=='LF',]$subjID))
```

**How many participants do we have per learning?** We have 41 for feature-label learning, and 39 for label-feature learning.

```
rm(fl,lf)
labelPicture <- generalizationLP[!(is.na(generalizationLP$resp)),]
n<- length(unique(labelPicture$subjID))
nrows <- (nrow(generalizationLP)) - (nrow(labelPicture))

sort(unique(labelPicture$subjID))-> subjs;
sort(unique(generalizationLP$subjID)) ->totsubjs;

subjmissed<- setdiff(totsubjs, subjs);
```

Great, we have 80 participants in this task, so -0, and we have missed 179 over the total 1920, that is 9.3229167. The subject(s) that missed completely the task is: .

**How many, what type of trials do we have?** How many datapoints did we lose for no-responses?

```
round(nrow(generalizationLP[(is.na(generalizationLP$resp)),])/nrow(generalizationLP)*100,2)
```

```
## [1] 9.32
```

How many trials were rt < 100?

```
round(nrow(generalizationLP[generalizationLP$rt<100,])/ nrow(generalizationLP)*100,2)
```

```
## [1] 9.38
```

Once trimmed, how many trials per participant do we have in this task?

```
labelPicture %>%
  group_by(subjID) %>%
  count() %>%
  filter(n<=18)
```

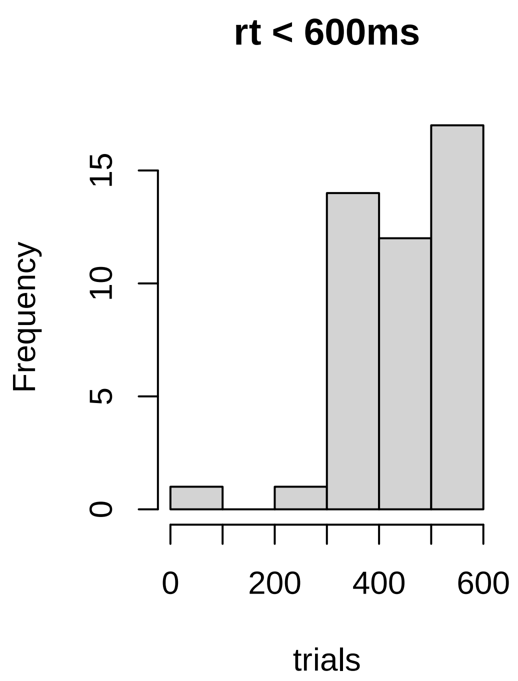
```
## # A tibble: 8 x 2
## # Groups:   subjID [8]
##    subjID     n
##     <int> <int>
## 1 1420577    18
## 2 1422475    18
## 3 1422477    17
## 4 1422677    17
## 5 1422680     9
## 6 1422689    17
## 7 1432009     8
## 8 1432075    17
```

Here we have less datapoints. For sure, 1422680 needs to be added to the black list because has few correct trials.

```
c(badsubjs, 1422680) -> badsubjs
```

```
par(mfrow=c(1,2))
hist(generalizationLP[generalizationLP$rt<600,]$rt, main = 'rt < 600ms', xlab = 'trials');
hist(generalizationLP[generalizationLP$rt>2000,]$rt, main = 'rt > 2000ms', xlab = 'trials');
```

**Check tails of the rt distribution**




```
par(mfrow=c(1,1))
```

```
rm(n, nrows, subjs, totsubjs);
labelPicture$acc <- 0;
labelPicture[labelPicture$category==1 & labelPicture$label=='dep',]$acc <- 1;
labelPicture[labelPicture$category==2 & labelPicture$label=='bim',]$acc <- 1;
labelPicture[labelPicture$category==3 & labelPicture$label=='tob',]$acc <- 1;
```

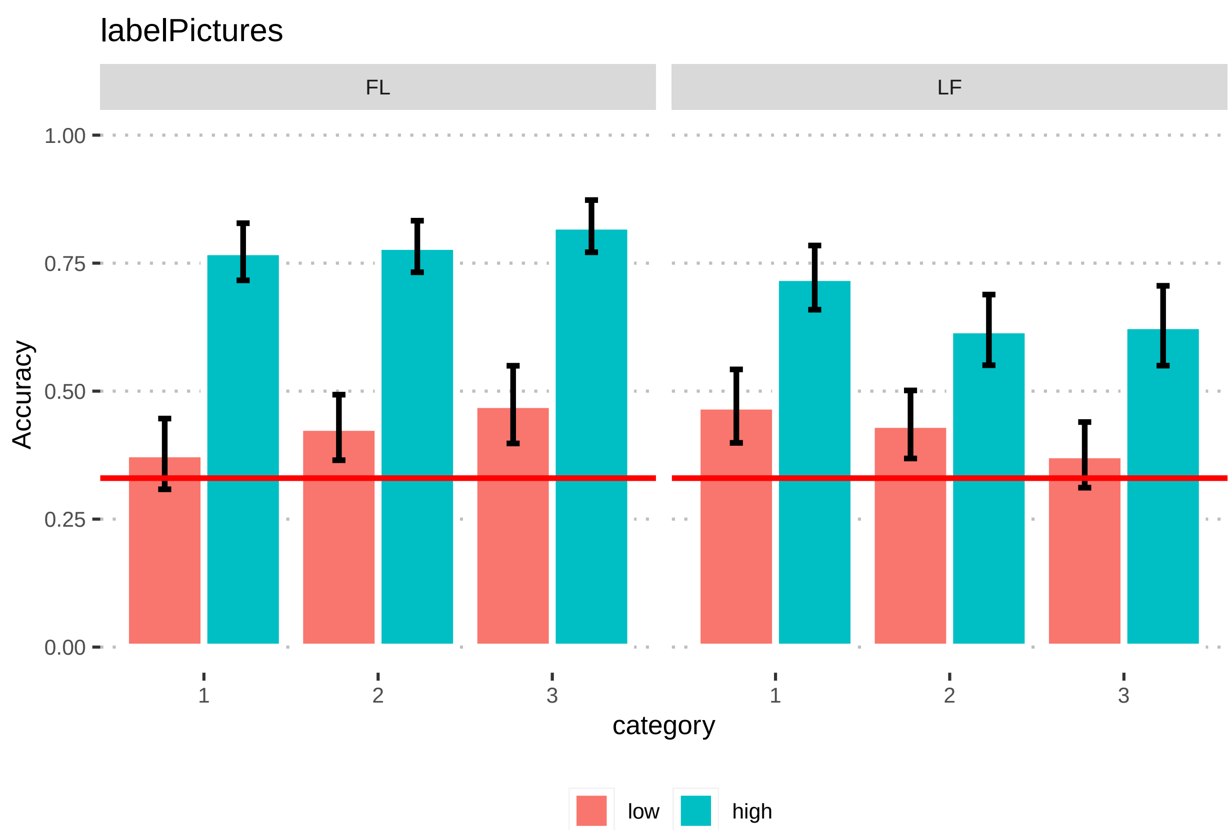
**Barplot accuracy by category+learning+frequency** Calculate the proportion of correct in each condition

```
rm(subjmissed)
ss_prop<-aggregate(acc ~ frequency+category+subjID+learning,
                   data = labelPicture[labelPicture$rt > 100 &
                                      !(labelPicture$subjID %in% badsubjs),], FUN = mean)
```

Plot aggregated over subjs. To see accuracy distributed over categories.

```
ms <- ss_prop %>%
  group_by(category, frequency, learning) %>%
  summarise(
    n=n(),
    mean=mean(acc),
    sd=sd(acc)
  ) %>%
  mutate( se=sd/sqrt(n))  %>%
  mutate( ci=se * qt((1-0.05)/2 + .5, n-1))
```

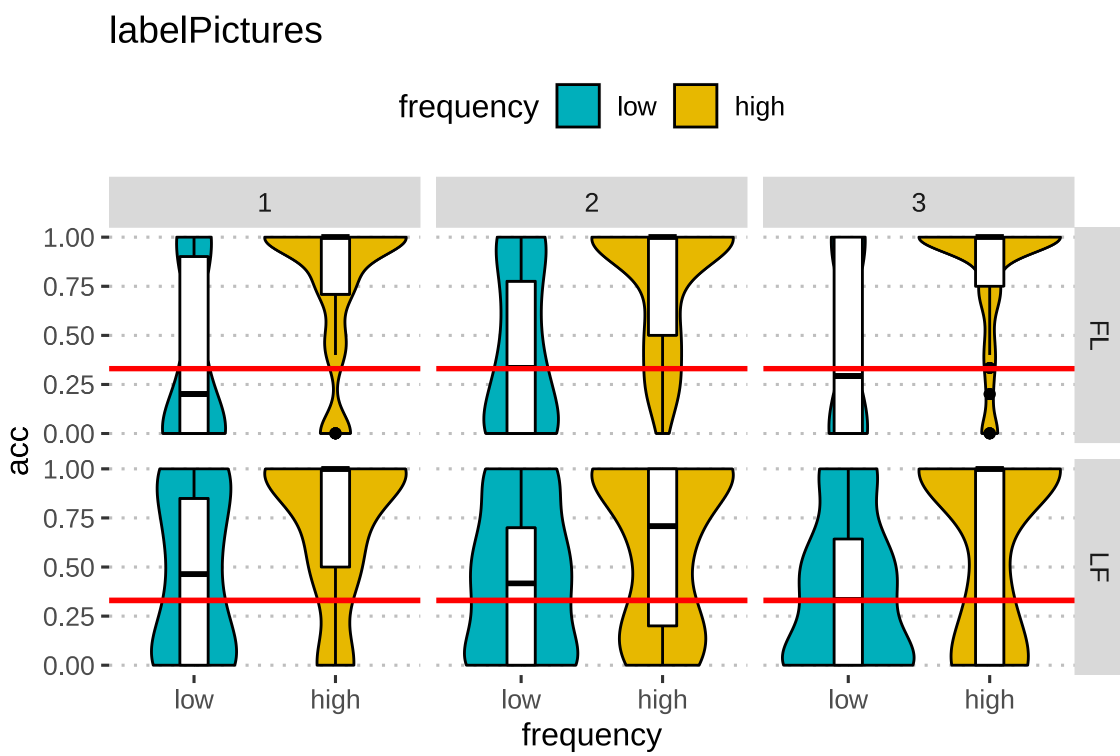
```
ms$frequency <- as.factor(ms$frequency)
plyr::revalue(ms$frequency, c("25"="low"))-> ms$frequency;
plyr::revalue(ms$frequency, c("75"="high"))-> ms$frequency;

ggplot(aes(x = category, y = mean, fill = frequency), data = ms) +
  facet_grid( . ~ learning) +
  geom_bar(stat = "identity", color='white', position=position_dodge(), size=1.2) +
  geom_errorbar(aes(ymin=mean-se, ymax=mean+se), width=.15, size=1,position=position_dodge(.9)) +
  ylab("Accuracy ") +
  xlab("category") +
  ggtitle('labelPictures') +
  coord_cartesian(ylim = c(0, 1))+
  ggpubr::theme_pubclean() +
  theme(legend.position="bottom", legend.title = element_blank()) +
  theme(text = element_text(size=10)) +
  geom_hline(yintercept = .33, col='red', lwd=1);
```




```
ms <- aggregate(acc ~ subjID+frequency+learning+category,
                data = labelPicture[labelPicture$rt > 100 &
                                    !(labelPicture$subjID %in% badsubjs),], mean)

ms$frequency <- as.factor(ms$frequency)
```

```r
plyr::revalue(ms$frequency, c("25"="low"))-> ms$frequency;
plyr::revalue(ms$frequency, c("75"="high"))-> ms$frequency;

ggviolin(ms, x = "frequency", y = "acc", fill = "frequency",
         palette = c("#00AFBB", "#E7B800"),
         add = "boxplot",
         add.params = list(fill = "white"),
         trim=TRUE) +
         ggtitle('labelPictures') +
        facet_grid( learning ~ category) +
        theme_pubclean()+
  geom_hline(yintercept = .33, col='red', lwd=1);
```

**Violin plot accuracy by category+learning+frequency**

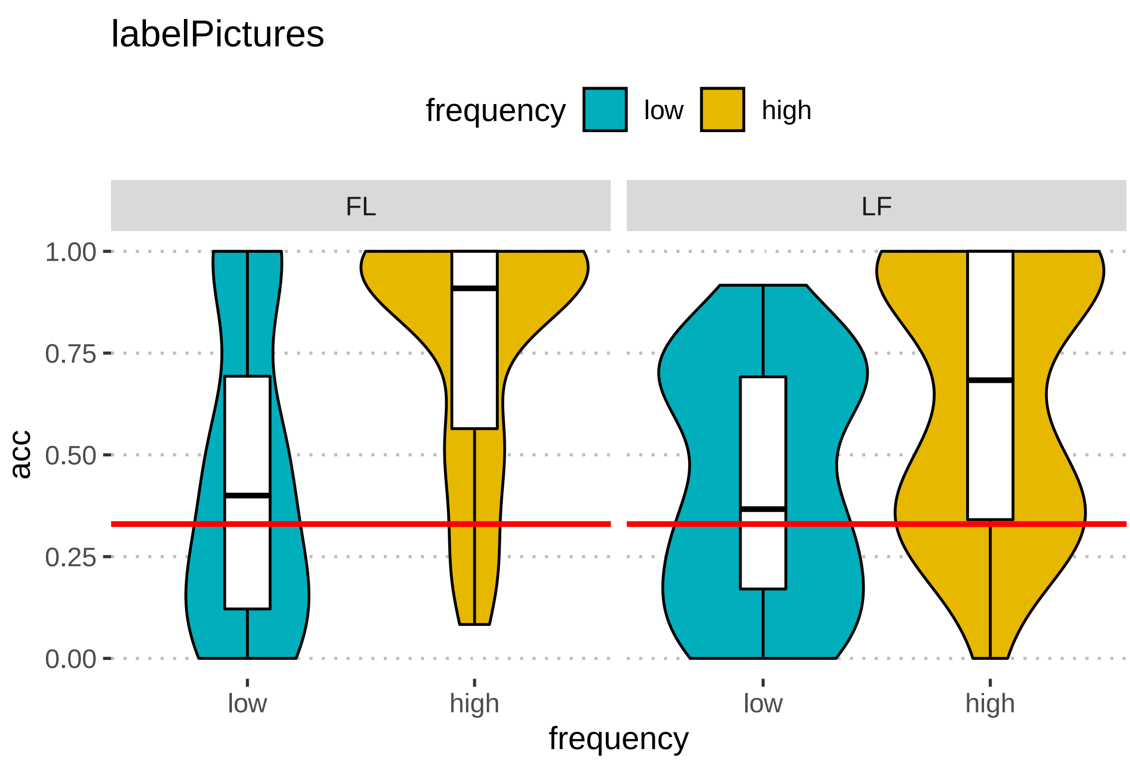



```r
#rm(ms, ss_prop)
```

```r
ms <- aggregate(acc ~ subjID+frequency+learning,
                data = labelPicture[labelPicture$rt > 100 &
                                         !(labelPicture$subjID %in% badsubjs),], mean)

ms$frequency <- as.factor(ms$frequency)
plyr::revalue(ms$frequency, c("25"="low"))-> ms$frequency;
plyr::revalue(ms$frequency, c("75"="high"))-> ms$frequency;
```

```r
ggviolin(ms, x = "frequency", y = "acc", fill = "frequency",
         palette = c("#00AFBB", "#E7B800"),
         add = "boxplot",
         add.params = list(fill = "white"),
         trim=TRUE) +
         ggtitle('labelPictures') +
        facet_grid( . ~ learning) +
        theme_pubclean()+
  geom_hline(yintercept = .33, col='red', lwd=1);
```

**Violinplot accuracy by learning+frequency**

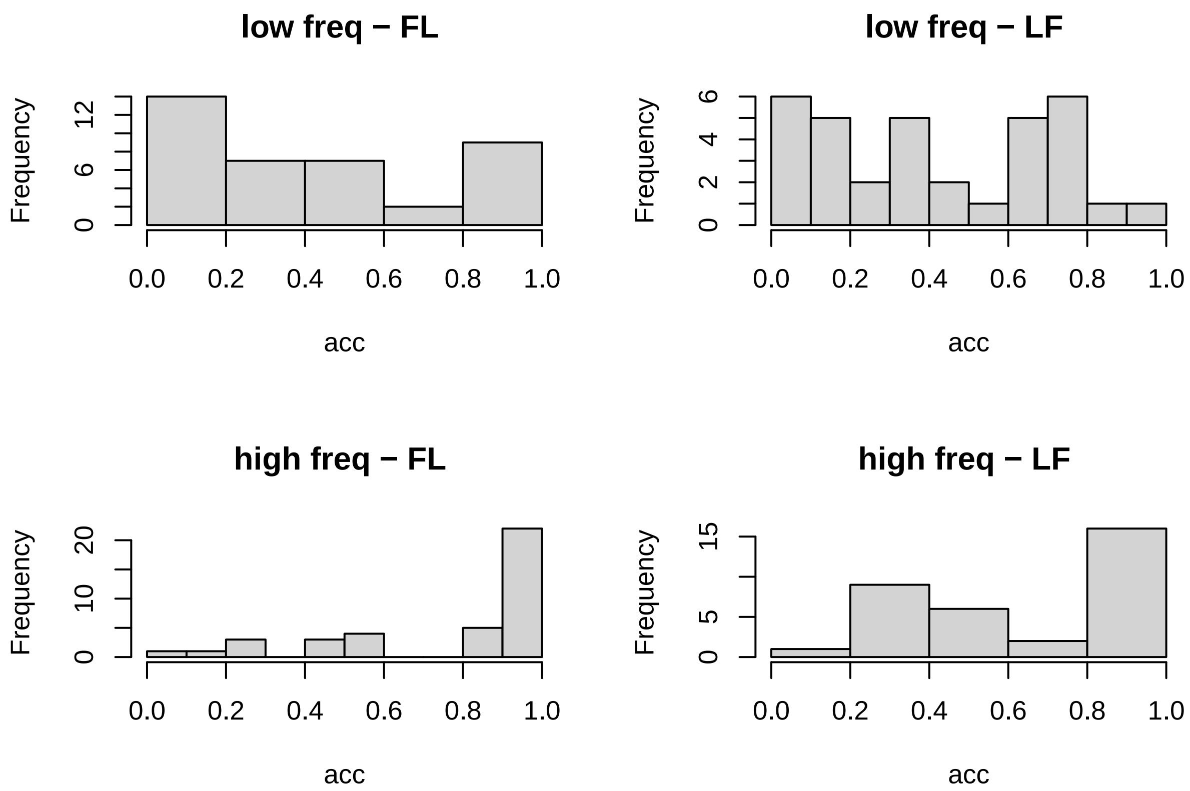



```r
#rm(ms, ss_prop)
```

```r
ms %>%
  group_by(learning, frequency) %>%
  summarise(mean(acc))
```

```
## # A tibble: 4 x 3
## # Groups:   learning [2]
##   learning frequency `mean(acc)`
##   <fct>    <fct>           <dbl>
## 1 FL       low             0.433
## 2 FL       high            0.780
## 3 LF       low             0.418
## 4 LF       high            0.648
```

```r
par(mfrow=c(2,2))
hist(ms[ms$frequency=='low' & ms$learning=='FL',]$acc, xlab = 'acc', main = 'low freq - FL ')
hist(ms[ms$frequency=='low' & ms$learning=='LF',]$acc, xlab = 'acc', main = 'low freq - LF ')
hist(ms[ms$frequency=='high' & ms$learning=='FL',]$acc, xlab = 'acc', main = 'high freq - FL ')
hist(ms[ms$frequency=='high' & ms$learning=='LF',]$acc, xlab = 'acc', main = 'high freq - LF ')
```




```r
par(mfrow=c(1,1))
```

```r
#barPlot aggregated over categories:

ms <- aggregate(acc ~ subjID+frequency+learning,
                data=labelPicture[labelPicture$rt > 100 &
                                  !(labelPicture$subjID %in% badsubjs)  ,], FUN= mean)

df<- ms %>%
  group_by(frequency, learning)%>%
  summarise(
    mean = mean(acc),
    sd = sd(acc),
    n = n()) %>%
  mutate( se=sd/sqrt(n))  %>%
  mutate( ci=se * qt((1-0.05)/2 + .5, n-1))
```

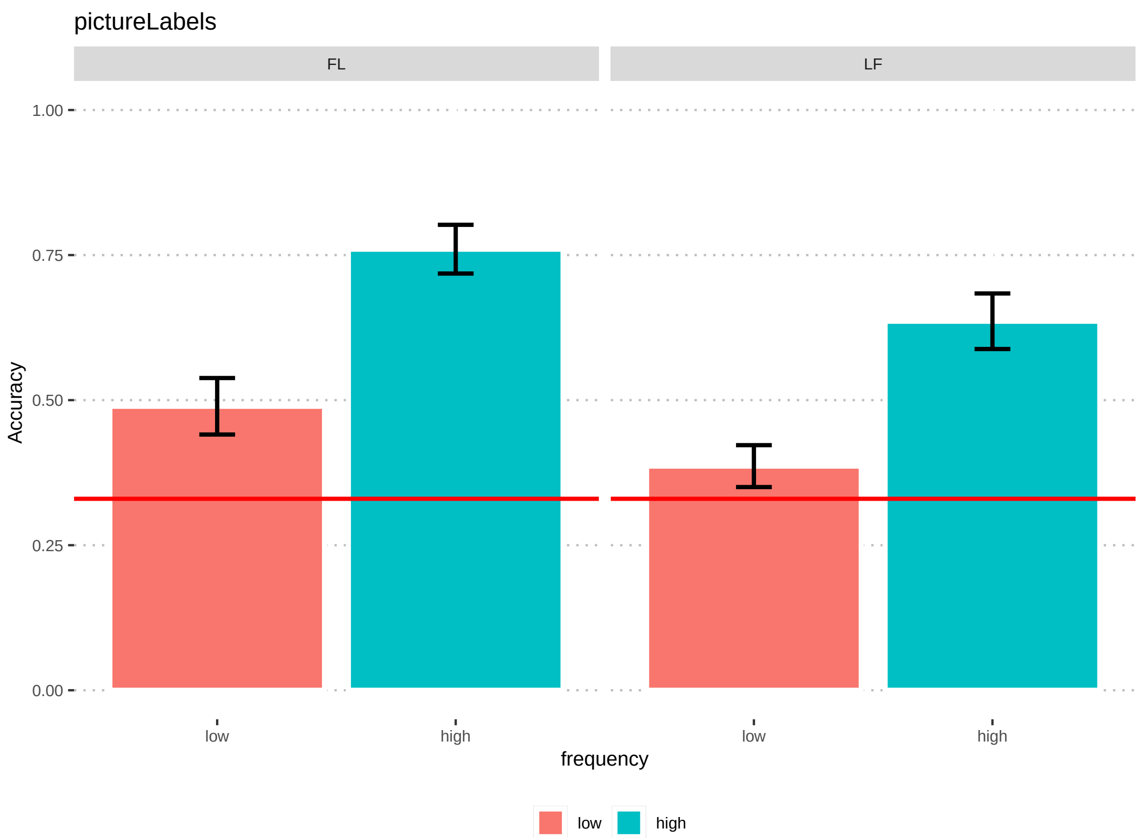
```r
df$frequency <- as.factor(df$frequency)
plyr::revalue(df$frequency, c("25"="low"))-> df$frequency;
plyr::revalue(df$frequency, c("75"="high"))-> df$frequency;


lp<-ggplot(aes(x = frequency, y = mean, fill = frequency), data = df) +
  facet_grid( . ~ learning) +
  geom_bar(stat = "identity", color='white', position=position_dodge(), size=1.2) +
  geom_errorbar(aes(ymin=mean-se, ymax=mean+se), width=.15, size=1,position=position_dodge(.9)) +
  ylab("Accuracy ") +
  xlab("frequency") +
  ggtitle('labelPictures') +
  coord_cartesian(ylim = c(0, 1))+
  ggpubr::theme_pubclean() +
  theme(legend.position="bottom", legend.title = element_blank()) +
  theme(text = element_text(size=10)) +
  geom_hline(yintercept = .33, col='red', lwd=1);
```

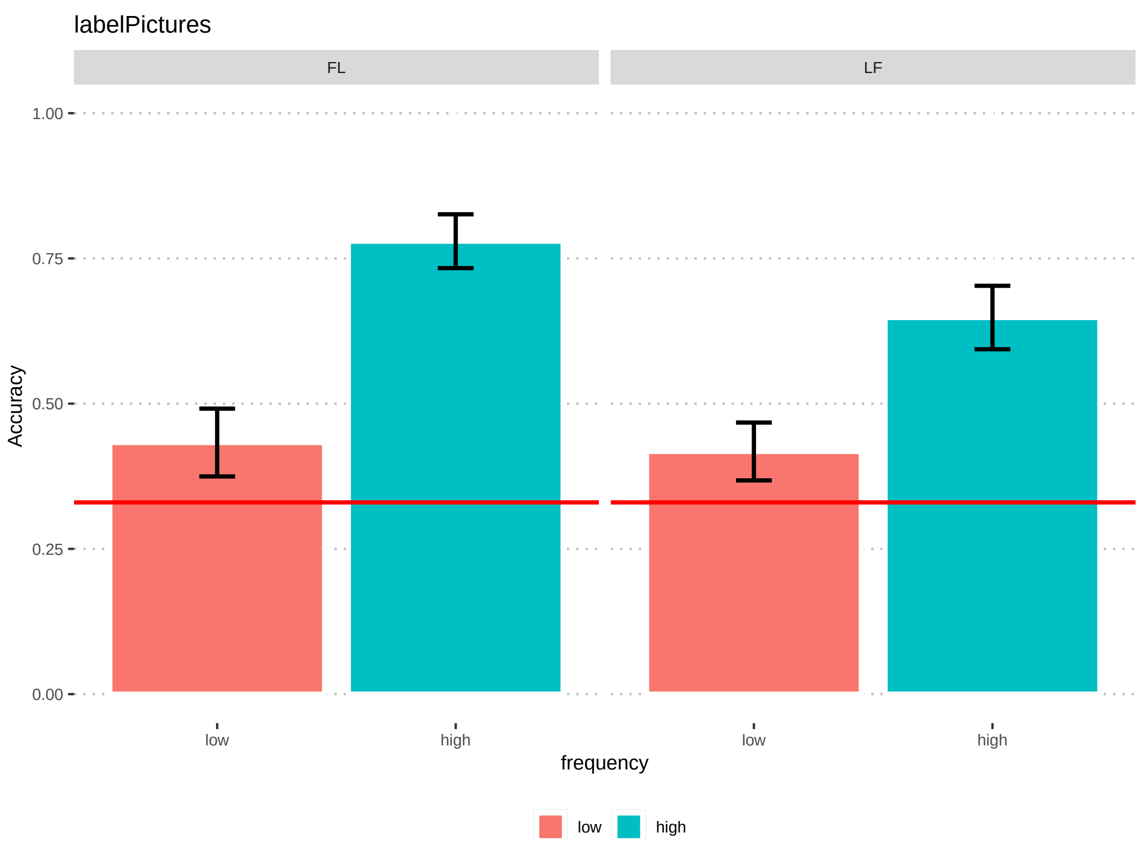
#### Barplot accuracy by frequency + learning

#### Comparison by frequency by learning by tasks

Quick summary of what we have so far:

```r
grid.arrange(pl,lp)
```


pictureLabels
FL
LF
1.00
0.75
0.50
0.25
0.00
Accuracy
low
high
low
high
frequency
low
high


labelPictures
FL
LF
1.00
0.75
0.50
0.25
0.00
Accuracy
low
high
low
high
frequency
low
high

What's going on in the low frequency condition? One way to see whether they simply learned another association is to check that wrong choices are distributed equally (50%) to the other two categories. If they are, then they didn't learn anything, but if they are not distributed equally, they have learned another association.

Label picture:

```
#select only inaccurate trials
temp <- labelPicture[labelPicture$acc==0,]

round(nrow(temp)/nrow(labelPicture)*100,2)
```

```
## [1] 43.83
```

How many of those are low frequency trials?

```
round(nrow(temp[temp$frequency==25,])/nrow(labelPicture)*100,2)
```

```
## [1] 28.49
```

Label picture task:

correct choice is listed in "label", that is, label presented. Participant's choice is listed in "category", that is, the fribble's category.

```
temp %>%
  filter(frequency=="25") %>%
  group_by(learning, label, category) %>%
  count()
```

```
## # A tibble: 12 x 4
## # Groups:   learning, label, category [12]
##    learning label category     n
##    <fct>    <fct>    <int> <int>
##  1 FL       bim          1    24
##  2 FL       bim          3    54
##  3 FL       dep          2    63
##  4 FL       dep          3    21
##  5 FL       tob          1    62
##  6 FL       tob          2    26
##  7 LF       bim          1     8
##  8 LF       bim          3    75
##  9 LF       dep          2    49
## 10 LF       dep          3    24
## 11 LF       tob          1    58
## 12 LF       tob          2    32
```

Nope, they definitely learned another association. The association they have learned is based on the high saliency feature, rather than on the low saliency one. Let's see if that is the case also for the other task:

Picture label task:

```r
#select only inaccurate trials
temp <- pictureLabel[pictureLabel$acc==0,]

round(nrow(temp)/nrow(pictureLabel)*100,2)
```

```
## [1] 44.28
```

How many of those are low frequency trials?

```r
round(nrow(temp[temp$frequency==25,])/nrow(pictureLabel)*100,2)
```

```
## [1] 28.92
```

Errors across tasks are comparable.

Picture label task:

correct choice is listed in “category”, that is, the category of the fribble presented. Participant’s choice is listed in “resp” column, that is, the label chosen.

```r
temp %>%
  filter(frequency=="25") %>%
  group_by(learning, category, resp) %>%
  count()
```

```
## # A tibble: 12 x 4
## # Groups:   learning, category, resp [12]
##    learning category resp      n
##    <fct>       <int> <fct> <int>
##  1 FL              1 bim      27
##  2 FL              1 tob      71
##  3 FL              2 dep      45
##  4 FL              2 tob      35
##  5 FL              3 bim      51
##  6 FL              3 dep      26
##  7 LF              1 bim      33
##  8 LF              1 tob      65
##  9 LF              2 dep      34
## 10 LF              2 tob      39
## 11 LF              3 bim      62
## 12 LF              3 dep      28
```

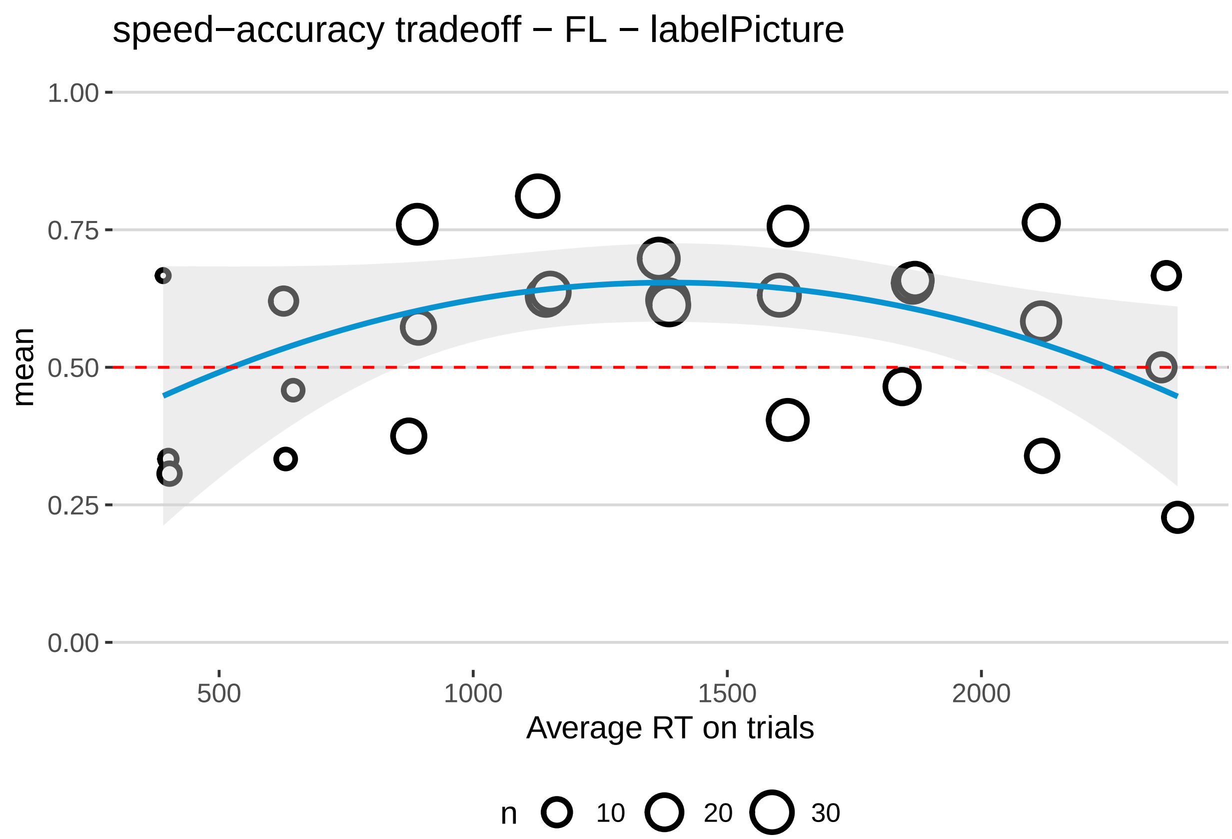
In both tasks participants were driven by the high salient feature in making errors, they simply learned only one association between the label and the high salient feature, and made decisions based on this.

## Speed-accuracy trade-off by tasks

Inspection of the speed-accuracy trade-off:

#### labelPicture

```
rt_range <- 2500
n_bins <- 10
break_seq <- seq(0, rt_range, rt_range/n_bins)

timeslice_range <- labelPicture[labelPicture$rt > 100 &
                                          !(labelPicture$subjID %in% badsubjs) ,] %>%
  filter(learning == "FL") %>%
  dplyr::mutate(RT_bin = cut(rt, breaks = break_seq)) %>%
  dplyr::group_by(RT_bin, category) %>%
  dplyr::mutate(RT_bin_avg = mean(rt, na.rm = T))

count_range <- timeslice_range %>%
  group_by(RT_bin, category) %>%
  summarise(subjcount = n_distinct(subjID), totalcount = n())

timeslice_range <- timeslice_range %>%
  dplyr::group_by(RT_bin_avg, category, subjID) %>%
  dplyr::summarise(ss_acc = mean(acc, na.rm=T)) %>%
  dplyr::group_by(RT_bin_avg, category) %>%
  dplyr::summarise(mean = mean(ss_acc),
            n = n())

ggplot(aes(x=RT_bin_avg, y=mean, weight = n),
           data = timeslice_range) +
  geom_point(aes(size = n), shape = 21, fill = "white", stroke = 1.5) +
  geom_smooth(method = "lm", formula = y ~ poly(x,2), se = TRUE, color = "#0892d0", fill = "lightgray")
  geom_hline(yintercept = 0.5, lty = "dashed", color = 'red') +
  coord_cartesian(ylim = c(0, 1))+
  ggthemes::theme_hc()+
  xlab("Average RT on trials") +
  ggtitle('speed-accuracy tradeoff - FL - labelPicture')
```

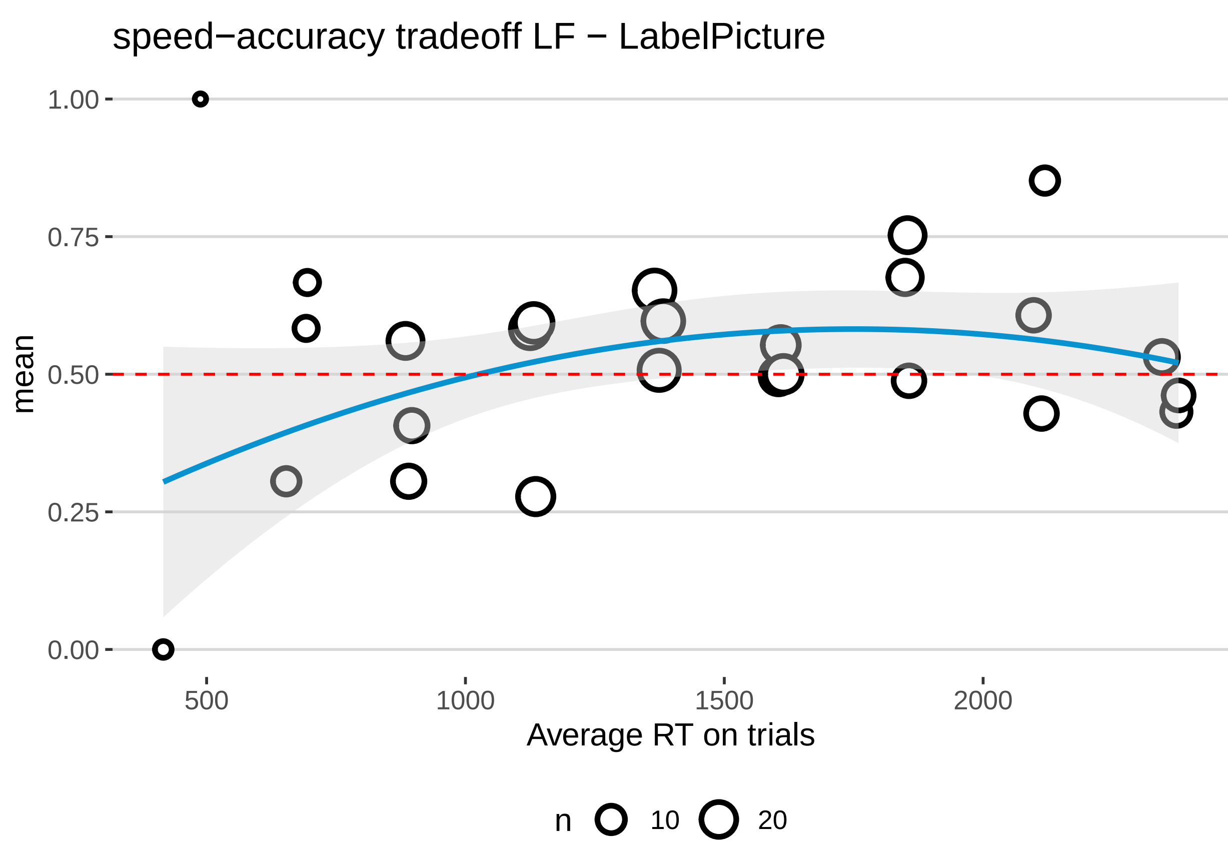



```
  ylab("Proportion Correct")
```

```
## $y
## [1] "Proportion Correct"
##
## attr(,"class")
## [1] "labels"
```

```
rt_range <- 2500
n_bins <- 10
break_seq <- seq(0, rt_range, rt_range/n_bins)

timeslice_range <- labelPicture[labelPicture$rt > 100 &
                                          !(labelPicture$subjID %in% badsubjs),] %>%
  filter(learning == "LF") %>%
  dplyr::mutate(RT_bin = cut(rt, breaks = break_seq)) %>%
  dplyr::group_by(RT_bin, category) %>%
  dplyr::mutate(RT_bin_avg = mean(rt, na.rm = T))

count_range <- timeslice_range %>%
  group_by(RT_bin, category) %>%
  summarise(subjcount = n_distinct(subjID), totalcount = n())

timeslice_range <- timeslice_range %>%
  dplyr::group_by(RT_bin_avg, category, subjID) %>%
```

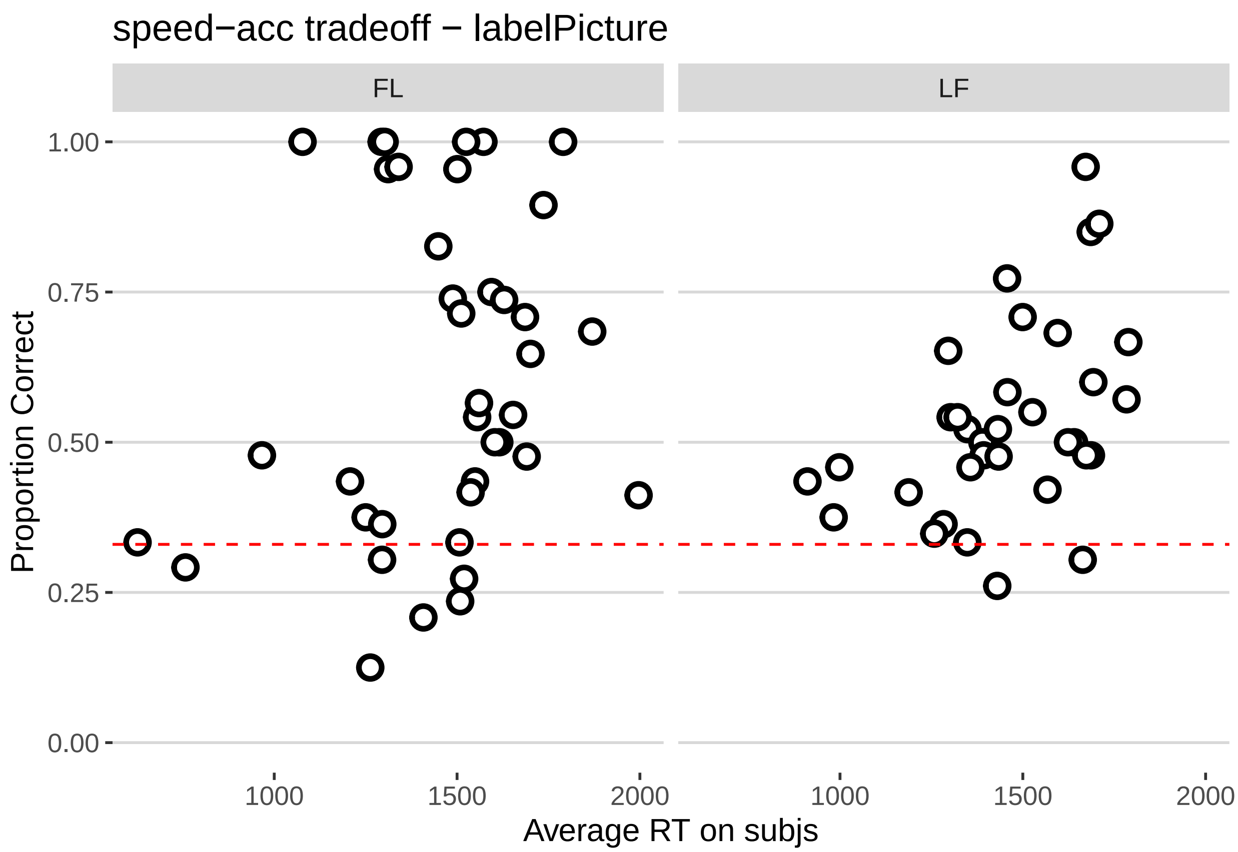
```
  dplyr::summarise(ss_acc = mean(acc, na.rm=T)) %>%
  dplyr::group_by(RT_bin_avg, category) %>%
  dplyr::summarise(mean = mean(ss_acc),
            n = n())

ggplot(aes(x=RT_bin_avg, y=mean, weight = n),
           data = timeslice_range) +
  geom_point(aes(size = n), shape = 21, fill = "white", stroke = 1.5) +
  geom_smooth(method = "lm", formula = y ~ poly(x,2), se = TRUE, color = "#0892d0", fill = "lightgray")
  geom_hline(yintercept = 0.5, lty = "dashed", color = 'red') +
  coord_cartesian(ylim = c(0, 1))+
  ggthemes::theme_hc()+
  xlab("Average RT on trials") +
  ggtitle('speed-accuracy tradeoff LF - LabelPicture')
```




```
  ylab("Proportion Correct")
```

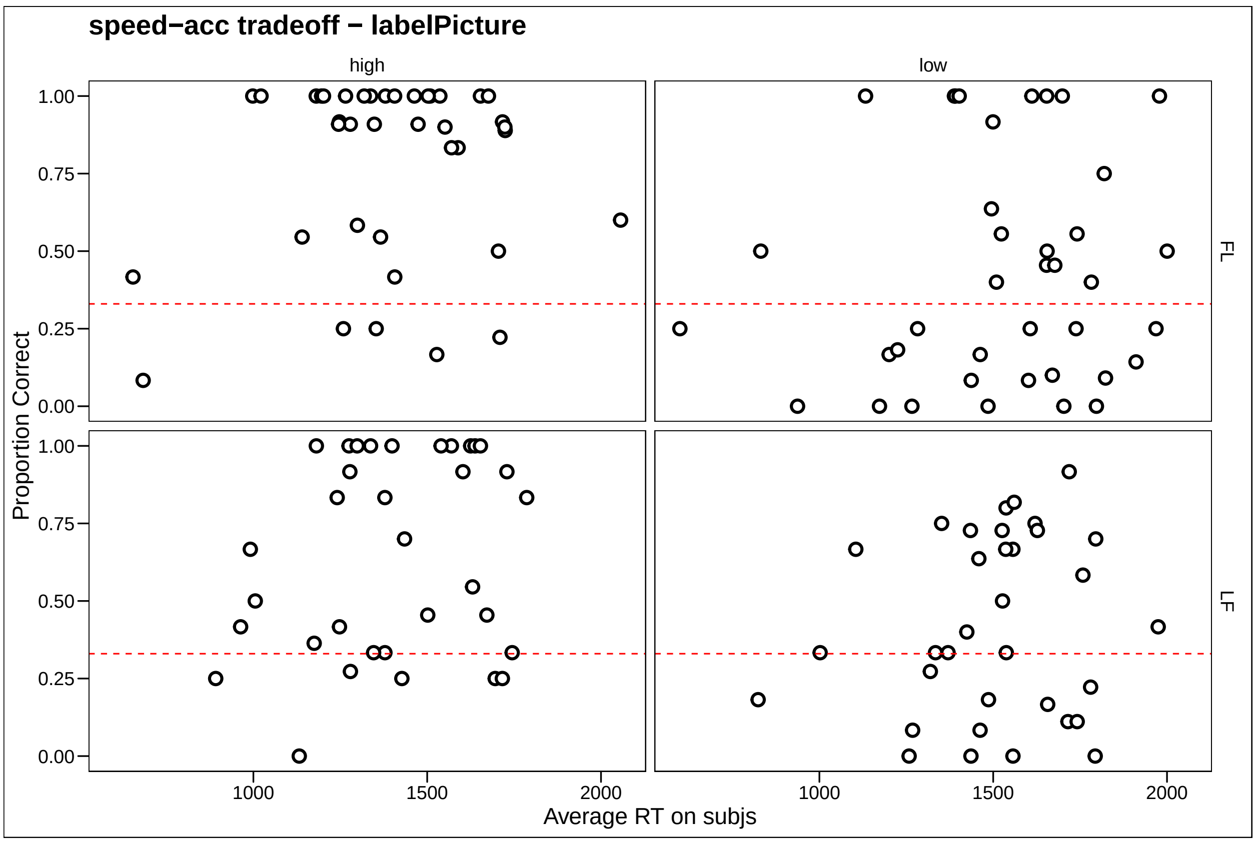
```
## $y
## [1] "Proportion Correct"
##
## attr(,"class")
## [1] "labels"
```

```
aggregate(acc ~ subjID+learning, labelPicture[labelPicture$rt > 100 &
                                         !(labelPicture$subjID %in% badsubjs) ,], mean)-> speedacc
aggregate(rt ~ subjID+learning, labelPicture[labelPicture$rt > 100 &
                                         !(labelPicture$subjID %in% badsubjs),], mean)-> speedacc2
merge(speedacc, speedacc2, by =  c("subjID", "learning"))-> speedacc

ggplot(aes(x=rt, y=acc),
           data = speedacc) +
  facet_grid( . ~ learning) +
  geom_point( shape = 21, fill = "white", size = 3, stroke = 1.5) +
  #geom_smooth(method = "lm", formula = y ~ poly(x,2), se = TRUE, color = "#0892d0", fill = "lightgray",
  geom_hline(yintercept = 0.33, lty = "dashed", color = 'red') +
  coord_cartesian(ylim = c(0, 1))+
  ggthemes::theme_hc()+
  xlab("Average RT on subjs") +
  ylab("Proportion Correct") +
  ggtitle("speed-acc tradeoff - labelPicture")
```




```
aggregate(acc ~ subjID+learning+frequency, labelPicture[labelPicture$rt > 100 &
                                         !(labelPicture$subjID %in% badsubjs) ,], mean)-> speedacc
aggregate(rt ~ subjID+learning+frequency, labelPicture[labelPicture$rt > 100 &
                                         !(labelPicture$subjID %in% badsubjs),], mean)-> speedacc2
merge(speedacc, speedacc2, by =  c("subjID", "learning", "frequency"))-> speedacc
rm(speedacc2)
dplyr::recode(speedacc$frequency, "25"="low", "75"="high")-> speedacc$frequency;
```

```r
ggplot(aes(x=rt, y=acc),
           data = speedacc) +
  facet_grid( learning ~ frequency) +
  geom_point( shape = 21, fill = "white", size = 3, stroke = 1.5) +
  #geom_smooth(method = "lm", formula = y ~ poly(x,2), se = TRUE, color = "#0892d0", fill = "lightgray"
  geom_hline(yintercept = 0.33, lty = "dashed", color = 'red') +
  coord_cartesian(ylim = c(0, 1))+
  ggthemes::theme_base()+
  xlab("Average RT on subjs") +
  ylab("Proportion Correct") +
  ggtitle("speed-acc tradeoff - labelPicture")
```

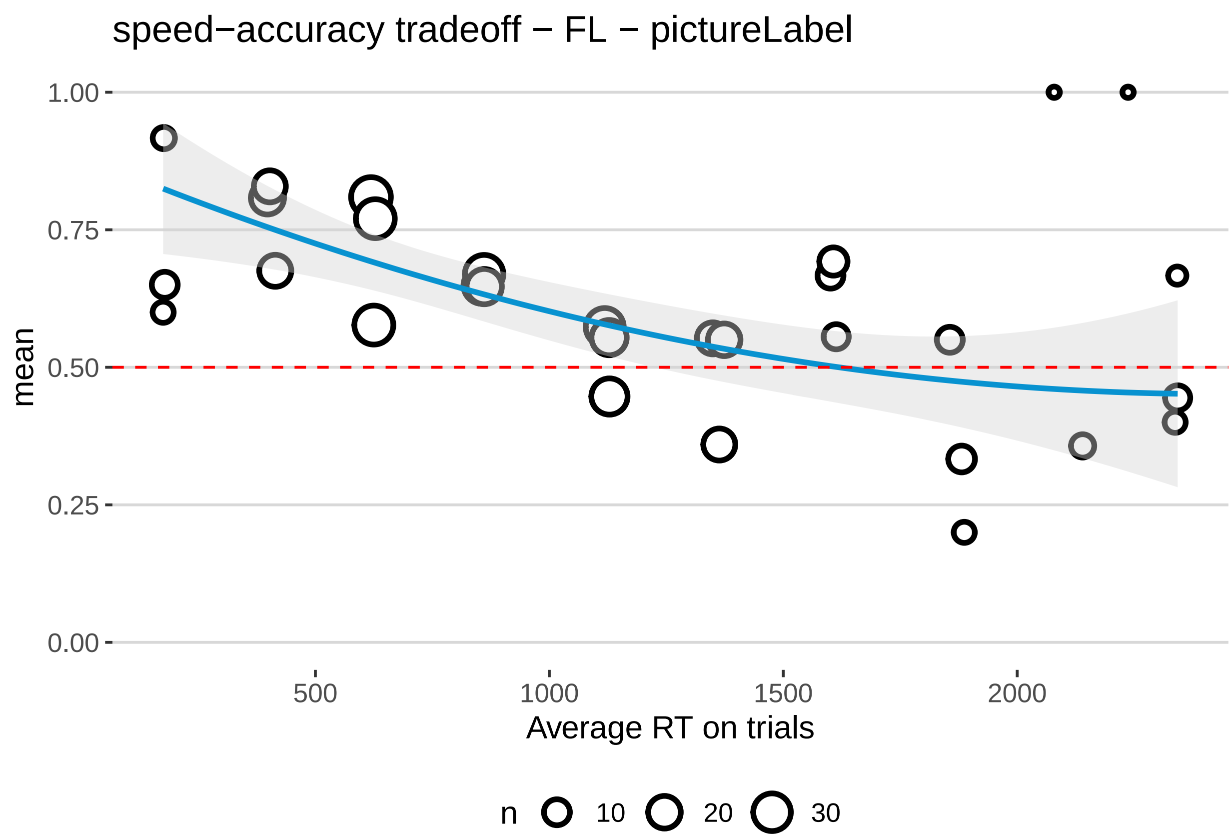



```r
speedacc %>%
  group_by(frequency, learning) %>%
  summarise(mean(rt), median(rt))
```

```
## # A tibble: 4 x 4
## # Groups:   frequency [2]
##   frequency learning `mean(rt)` `median(rt)`
##   <chr>     <fct>         <dbl>        <dbl>
## 1 high      FL            1392.        1380.
## 2 high      LF            1405.        1389.
## 3 low       FL            1521.        1602.
## 4 low       LF            1502.        1531.
```

**PictureLabel**

```
rt_range <- 2500
n_bins <- 10
break_seq <- seq(0, rt_range, rt_range/n_bins)

timeslice_range <- pictureLabel[pictureLabel$rt > 100 &
                                  !(pictureLabel$subjID %in% badsubjs),] %>%
  filter(learning == "FL") %>%
  dplyr::mutate(RT_bin = cut(rt, breaks = break_seq)) %>%
  dplyr::group_by(RT_bin, category) %>%
  dplyr::mutate(RT_bin_avg = mean(rt, na.rm = T))

count_range <- timeslice_range %>%
  group_by(RT_bin, category) %>%
  summarise(subjcount = n_distinct(subjID), totalcount = n())

timeslice_range <- timeslice_range %>%
  dplyr::group_by(RT_bin_avg, category, subjID) %>%
  dplyr::summarise(ss_acc = mean(acc, na.rm=T)) %>%
  dplyr::group_by(RT_bin_avg, category) %>%
  dplyr::summarise(mean = mean(ss_acc),
                   n = n())

ggplot(aes(x=RT_bin_avg, y=mean, weight = n),
           data = timeslice_range) +
  geom_point(aes(size = n), shape = 21, fill = "white", stroke = 1.5) +
  geom_smooth(method = "lm", formula = y ~ poly(x,2), se = TRUE, color = "#0892d0", fill = "lightgray")
  geom_hline(yintercept = 0.5, lty = "dashed", color = 'red') +
  coord_cartesian(ylim = c(0, 1))+
  ggthemes::theme_hc()+
  xlab("Average RT on trials") +
  ggtitle('speed-accuracy tradeoff - FL - pictureLabel')
```

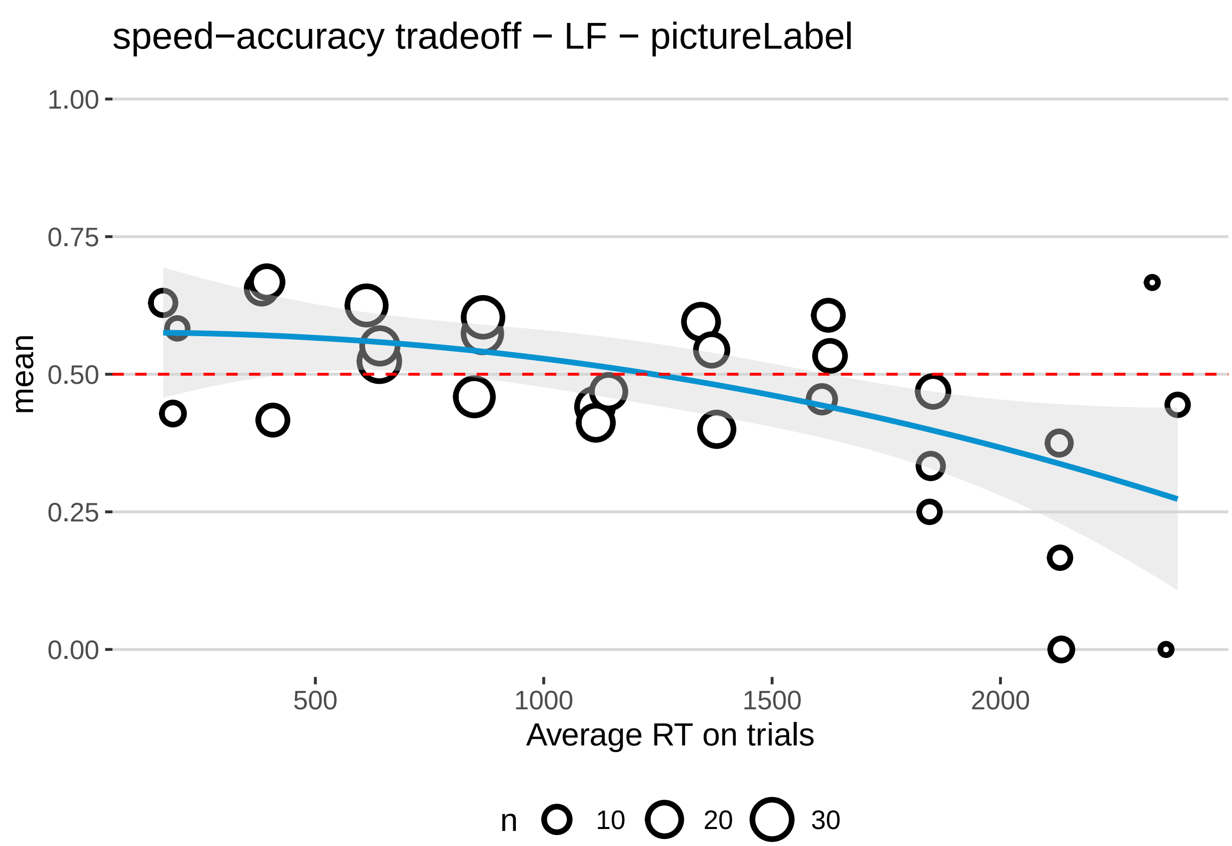



```
  ylab("Proportion Correct")
```

```
## $y
## [1] "Proportion Correct"
##
## attr(,"class")
## [1] "labels"
```

```
rt_range <- 2500
n_bins <- 10
break_seq <- seq(0, rt_range, rt_range/n_bins)

timeslice_range <- pictureLabel[pictureLabel$rt > 100  &
                                          !(pictureLabel$subjID %in% badsubjs),] %>%
  filter(learning == "LF") %>%
  dplyr::mutate(RT_bin = cut(rt, breaks = break_seq)) %>%
  dplyr::group_by(RT_bin, category) %>%
  dplyr::mutate(RT_bin_avg = mean(rt, na.rm = T))

count_range <- timeslice_range %>%
  group_by(RT_bin, category) %>%
  summarise(subjcount = n_distinct(subjID), totalcount = n())

timeslice_range <- timeslice_range %>%
  dplyr::group_by(RT_bin_avg, category, subjID) %>%
```

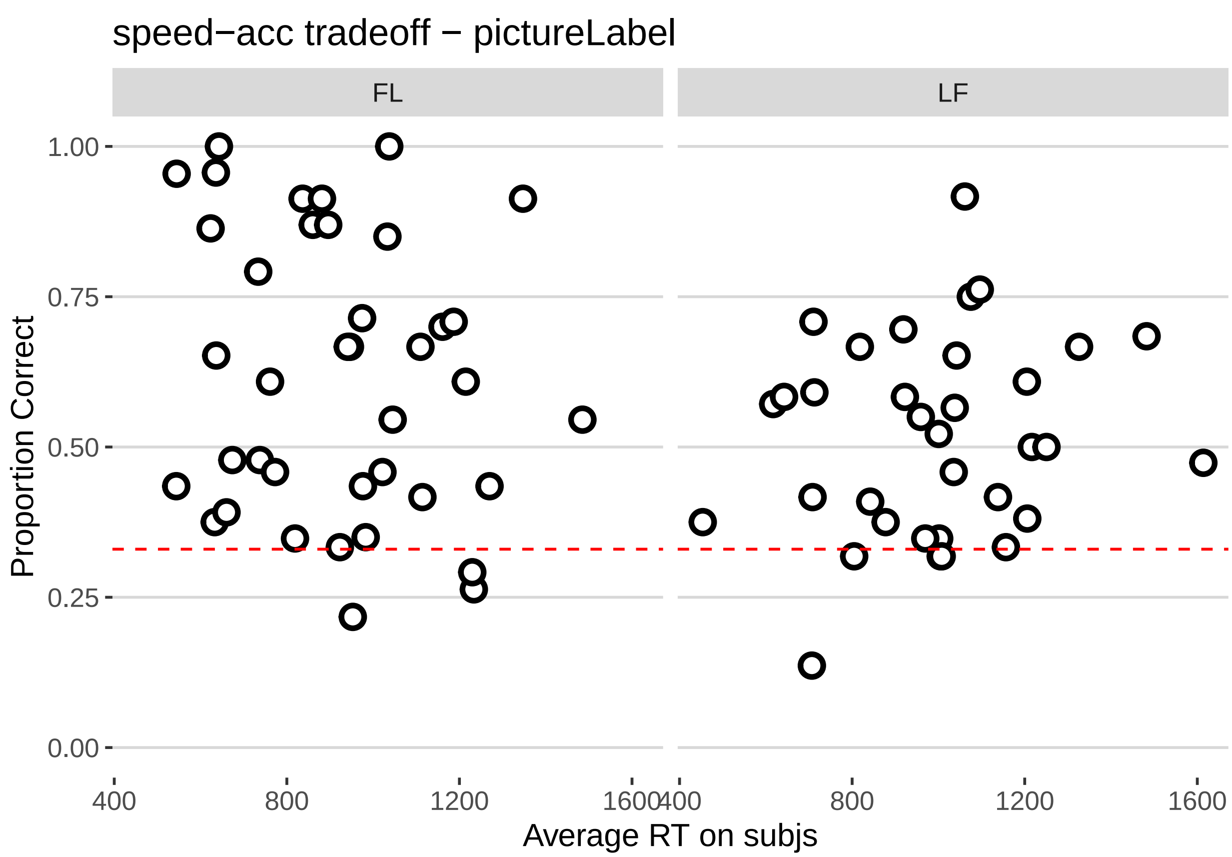
```
  dplyr::summarise(ss_acc = mean(acc, na.rm=T)) %>%
  dplyr::group_by(RT_bin_avg, category) %>%
  dplyr::summarise(mean = mean(ss_acc),
            n = n())

ggplot(aes(x=RT_bin_avg, y=mean, weight = n),
           data = timeslice_range) +
  geom_point(aes(size = n), shape = 21, fill = "white", stroke = 1.5) +
  geom_smooth(method = "lm", formula = y ~ poly(x,2), se = TRUE, color = "#0892d0", fill = "lightgray")
  geom_hline(yintercept = 0.5, lty = "dashed", color = 'red') +
  coord_cartesian(ylim = c(0, 1))+
  ggthemes::theme_hc()+
  xlab("Average RT on trials") +
  ggtitle('speed-accuracy tradeoff - LF - pictureLabel')
```




```
  ylab("Proportion Correct")
```

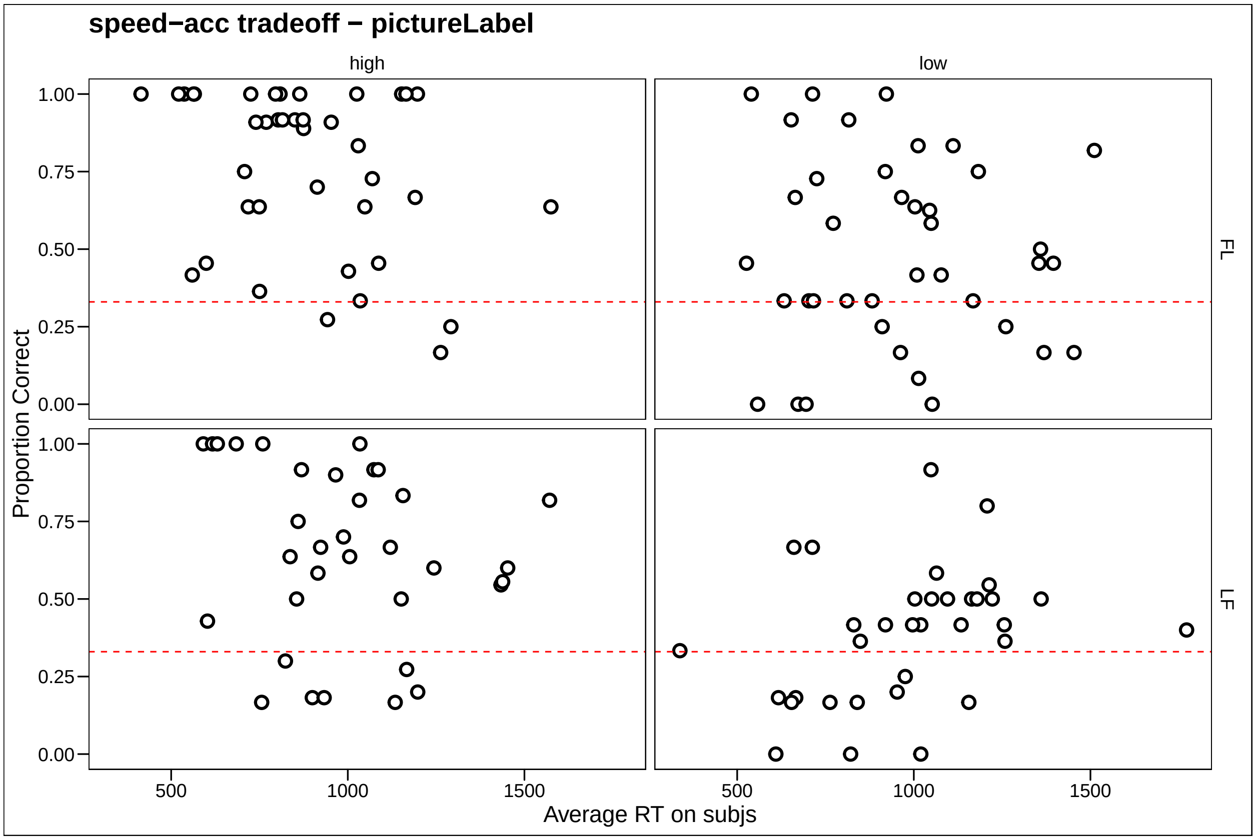
```
## $y
## [1] "Proportion Correct"
##
## attr(,"class")
## [1] "labels"
```

```r
aggregate(acc ~ subjID+learning, pictureLabel[pictureLabel$rt > 100  &
                                        !(pictureLabel$subjID %in% badsubjs),], mean)-> speedacc
aggregate(rt ~ subjID+learning, pictureLabel[pictureLabel$rt > 100  &
                                        !(pictureLabel$subjID %in% badsubjs),], mean)-> speedacc2
merge(speedacc, speedacc2, by =  c("subjID", "learning"))-> speedacc

ggplot(aes(x=rt, y=acc),
           data = speedacc) +
  facet_grid( . ~ learning) +
  geom_point( shape = 21, fill = "white", size = 3, stroke = 1.5) +
  #geom_smooth(method = "lm", formula = y ~ poly(x,2), se = TRUE, color = "#0892d0", fill = "lightgray"
  geom_hline(yintercept = 0.33, lty = "dashed", color = 'red') +
  coord_cartesian(ylim = c(0, 1))+
  ggthemes::theme_hc()+
  xlab("Average RT on subjs") +
  ylab("Proportion Correct") +
  ggtitle("speed-acc tradeoff - pictureLabel")
```




```r
aggregate(acc ~ subjID+learning+frequency, pictureLabel[pictureLabel$rt > 100  &
                                        !(pictureLabel$subjID %in% badsubjs),], mean)-> speedacc
aggregate(rt ~ subjID+learning+frequency, pictureLabel[pictureLabel$rt > 100  &
                                        !(pictureLabel$subjID %in% badsubjs),], mean)-> speedacc2
merge(speedacc, speedacc2, by =  c("subjID", "learning", "frequency"))-> speedacc
rm(speedacc2)
dplyr::recode(speedacc$frequency, "25"="low", "75"="high")-> speedacc$frequency;
```

```r
ggplot(aes(x=rt, y=acc),
           data = speedacc) +
  facet_grid( learning ~ frequency) +
  geom_point( shape = 21, fill = "white", size = 3, stroke = 1.5) +
  #geom_smooth(method = "lm", formula = y ~ poly(x,2), se = TRUE, color = "#0892d0", fill = "lightgray"
  geom_hline(yintercept = 0.33, lty = "dashed", color = 'red') +
  coord_cartesian(ylim = c(0, 1))+
  ggthemes::theme_base()+
  xlab("Average RT on subjs") +
  ylab("Proportion Correct") +
  ggtitle("speed-acc tradeoff - pictureLabel")
```




```r
speedacc %>%
  group_by(frequency, learning) %>%
  summarise(mean(rt), median(rt))
```

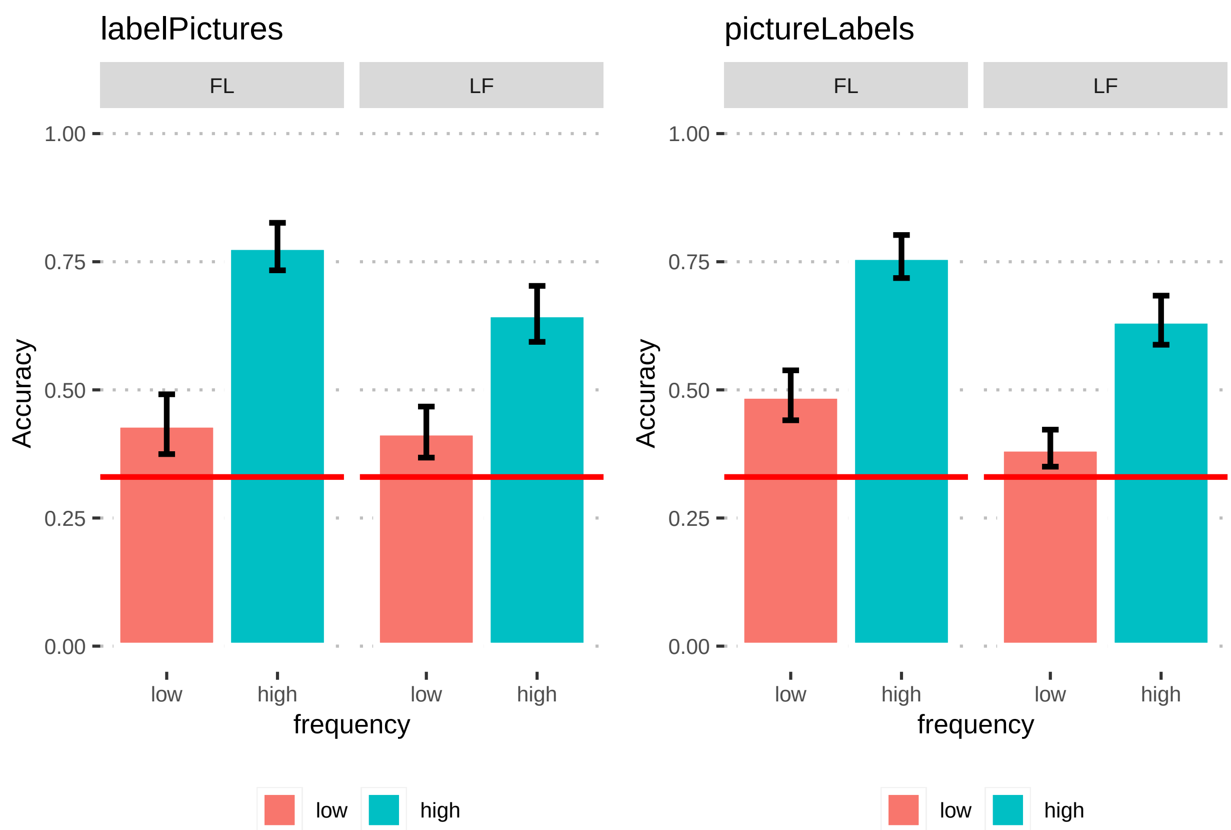
```
## # A tibble: 4 x 4
## # Groups:   frequency [2]
##   frequency learning `mean(rt)` `median(rt)`
##   <chr>     <fct>         <dbl>        <dbl>
## 1 high      FL             886.         864.
## 2 high      LF             994.         977.
## 3 low       FL             953.         962.
## 4 low       LF             983.        1011.
```

### Comparisons by tasks + learning + frequency

Barplot labelPicture

```
ms <- aggregate(acc ~ subjID+frequency+learning,
                data=labelPicture[labelPicture$rt > 100  &
                                         !(labelPicture$subjID %in% badsubjs),], FUN= mean)

df<- ms %>%
  group_by(frequency, learning)%>%
  summarise(
    mean = mean(acc),
    sd = sd(acc),
    n = n()) %>%
  mutate( se=sd/sqrt(n))  %>%
  mutate( ci=se * qt((1-0.05)/2 + .5, n-1))

df$frequency <- as.factor(df$frequency)
plyr::revalue(df$frequency, c("25"="low"))-> df$frequency;
plyr::revalue(df$frequency, c("75"="high"))-> df$frequency;


lp<-ggplot(aes(x = frequency, y = mean, fill = frequency), data = df) +
  facet_grid( . ~ learning) +
  geom_bar(stat = "identity", color='white', position=position_dodge(), size=1.2) +
  geom_errorbar(aes(ymin=mean-se, ymax=mean+se), width=.15, size=1,position=position_dodge(.9)) +
  ylab("Accuracy ") +
  xlab("frequency") +
  ggtitle("labelPictures") +
  coord_cartesian(ylim = c(0, 1))+
  ggpubr::theme_pubclean() +
  theme(legend.position="bottom", legend.title = element_blank()) +
  theme(text = element_text(size=10)) +
  geom_hline(yintercept = .33, col='red', lwd=1);
```

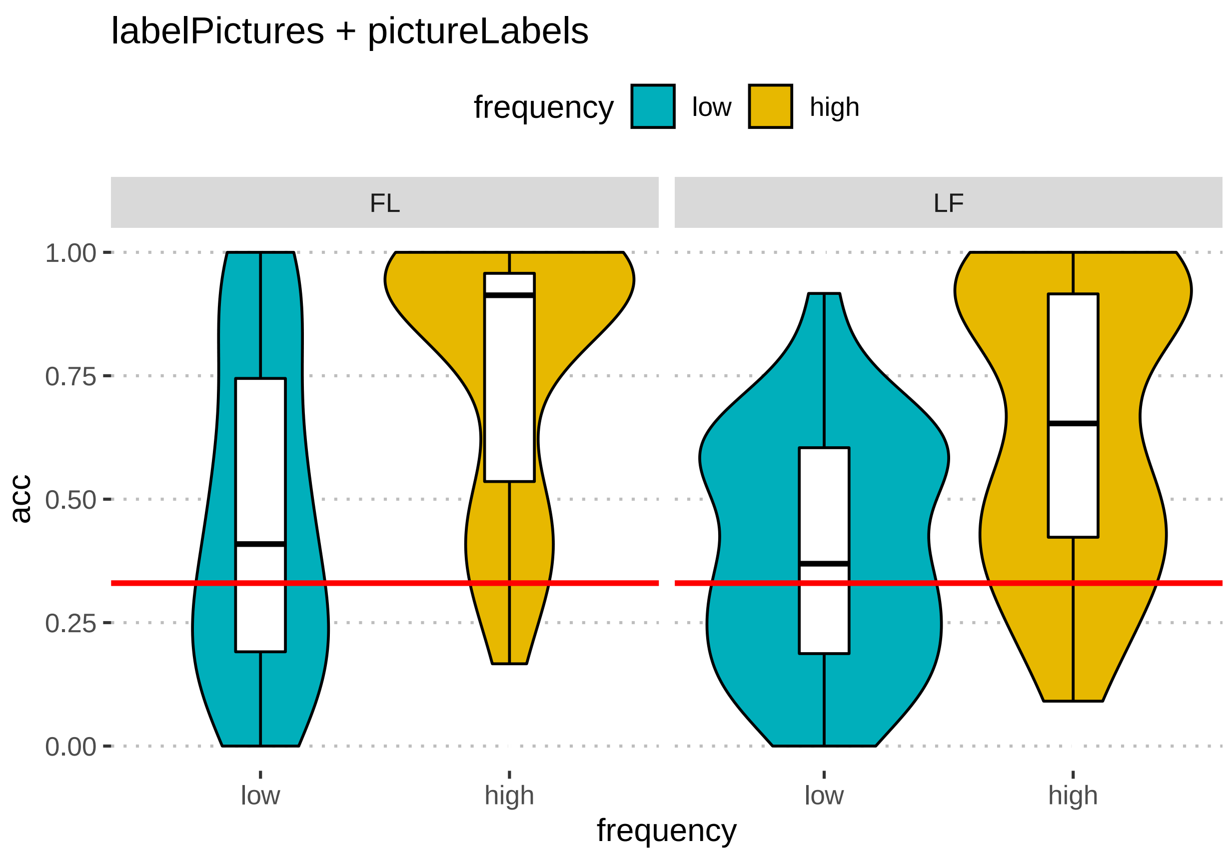
```
grid.arrange(lp, pl, ncol=2)
```




Barplots + violinPlots with data from both tasks:

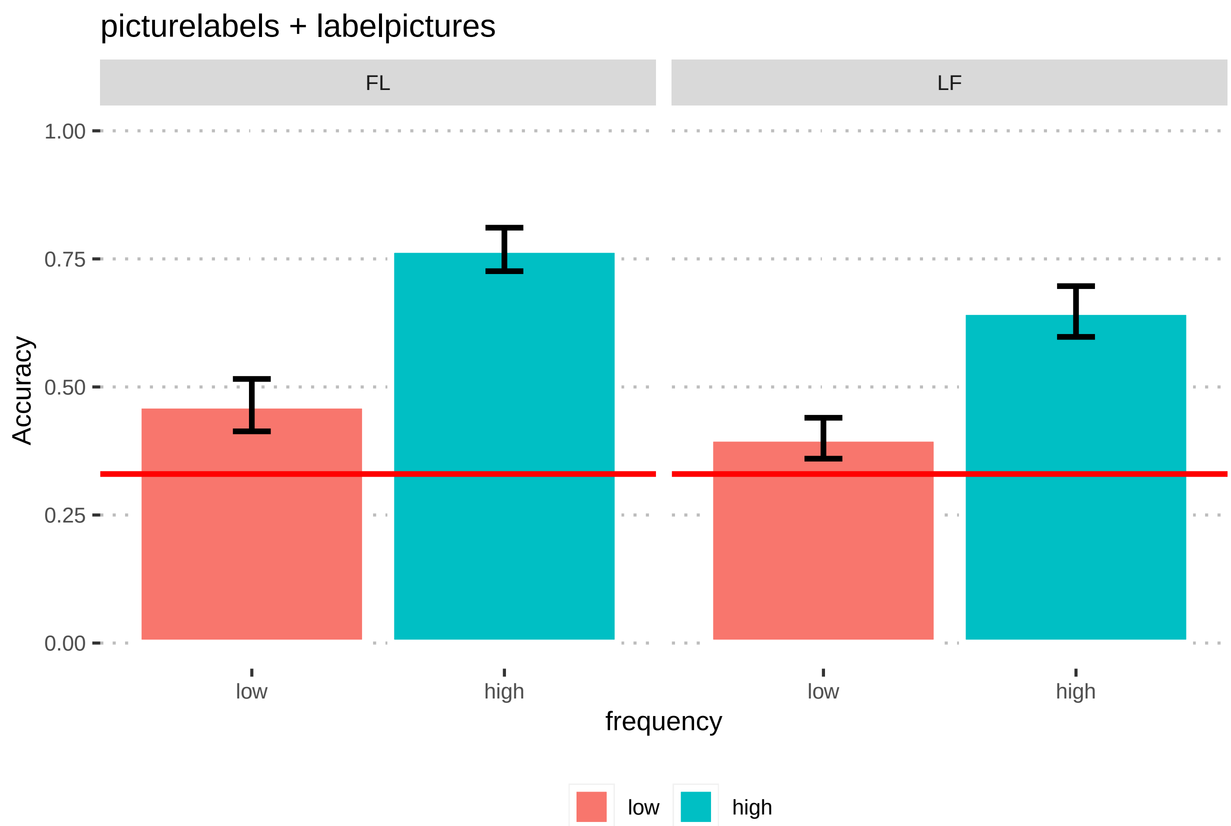
```
rm(ms, lp, pl, df, ss_prop)
genTask <- rbind(labelPicture, pictureLabel)
```

```
ms <- aggregate(acc ~ subjID+frequency+learning, data = genTask[genTask$rt>100 &
                                             !(genTask$subjID %in% badsubjs),], mean)

ms$frequency <- as.factor(ms$frequency)
plyr::revalue(ms$frequency, c("25"="low"))-> ms$frequency;
plyr::revalue(ms$frequency, c("75"="high"))-> ms$frequency;

ggviolin(ms, x = "frequency", y = "acc", fill = "frequency",
         palette = c("#00AFBB", "#E7B800"),
         add = "boxplot",
         add.params = list(fill = "white"),
         trim=TRUE) +
        ggtitle('labelPictures + pictureLabels') +
        facet_grid( . ~ learning) +
        theme_pubclean()+
  geom_hline(yintercept = .33, col='red', lwd=1);
```




```
ms <- aggregate(acc ~ subjID+frequency+learning, data=genTask[genTask$rt>100 &
                                                    !(genTask$subjID %in% badsubjs),], FUN= mean)

df<- ms %>%
  group_by(frequency, learning)%>%
  summarise(
    mean = mean(acc),
    sd = sd(acc),
    n = n()) %>%
  mutate( se=sd/sqrt(n))  %>%
  mutate( ci=se * qt((1-0.05)/2 + .5, n-1))

df$frequency <- as.factor(df$frequency)
plyr::revalue(df$frequency, c("25"="low"))-> df$frequency;
plyr::revalue(df$frequency, c("75"="high"))-> df$frequency;


ggplot(aes(x = frequency, y = mean, fill = frequency), data = df) +
  facet_grid( . ~ learning) +
  geom_bar(stat = "identity", color='white', position=position_dodge(), size=1.2) +
  geom_errorbar(aes(ymin=mean-se, ymax=mean+se), width=.15, size=1,position=position_dodge(.9)) +
  ylab("Accuracy ") +
  xlab("frequency") +
  ggtitle("labelPicture") +
  ggtitle('picturelabels + labelpictures') +
  coord_cartesian(ylim = c(0, 1))+
```

```
  ggpubr::theme_pubclean() +
  theme(legend.position="bottom", legend.title = element_blank()) +
  theme(text = element_text(size=10)) +
  geom_hline(yintercept = .33, col='red', lwd=1);
```




**Task 3: Contingency judgement**

```
length(unique(contingencyJudgement$subjID))
```

```
## [1] 80
```

```
fl<- length(unique(contingencyJudgement[contingencyJudgement$learning=='FL',]$subjID))
lf<- length(unique(contingencyJudgement[contingencyJudgement$learning=='LF',]$subjID))
```

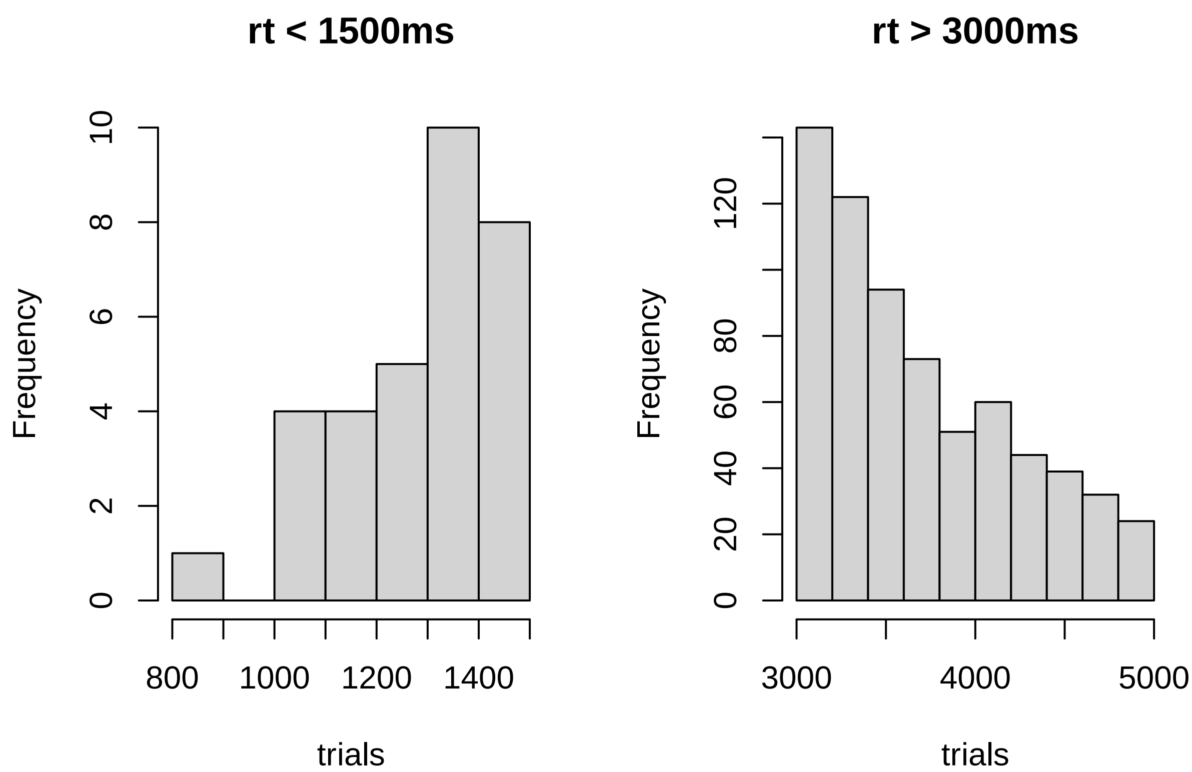
We have 41 for feature-label learning, and 39 for label-feature learning.

```
rm(fl,lf)
conjudge <- contingencyJudgement[!(is.na(contingencyJudgement$resp)),]
n<- length(unique(conjudge$subjID))
nrows <- (nrow(contingencyJudgement)) - (nrow(conjudge))

sort(unique(conjudge$subjID))-> subjs;
```

```r
sort(unique(contingencyJudgement$subjID)) ->totsubjs;

subjmissed<- setdiff(totsubjs, subjs);
```

We have 74 participants in this task, so -6, and we have missed 382 over the total 1920, that is 19.8958333. The subject(s) that missed completely the task is/are: 1414932, 1420171, 1420199, 1422475, 1431960, 1431997.

```r
par(mfrow=c(1,2))
hist(conjudge[conjudge$rt<1500,]$rt, main = 'rt < 1500ms', xlab = 'trials');
hist(conjudge[conjudge$rt>3000,]$rt, main = 'rt > 3000ms', xlab = 'trials');
```

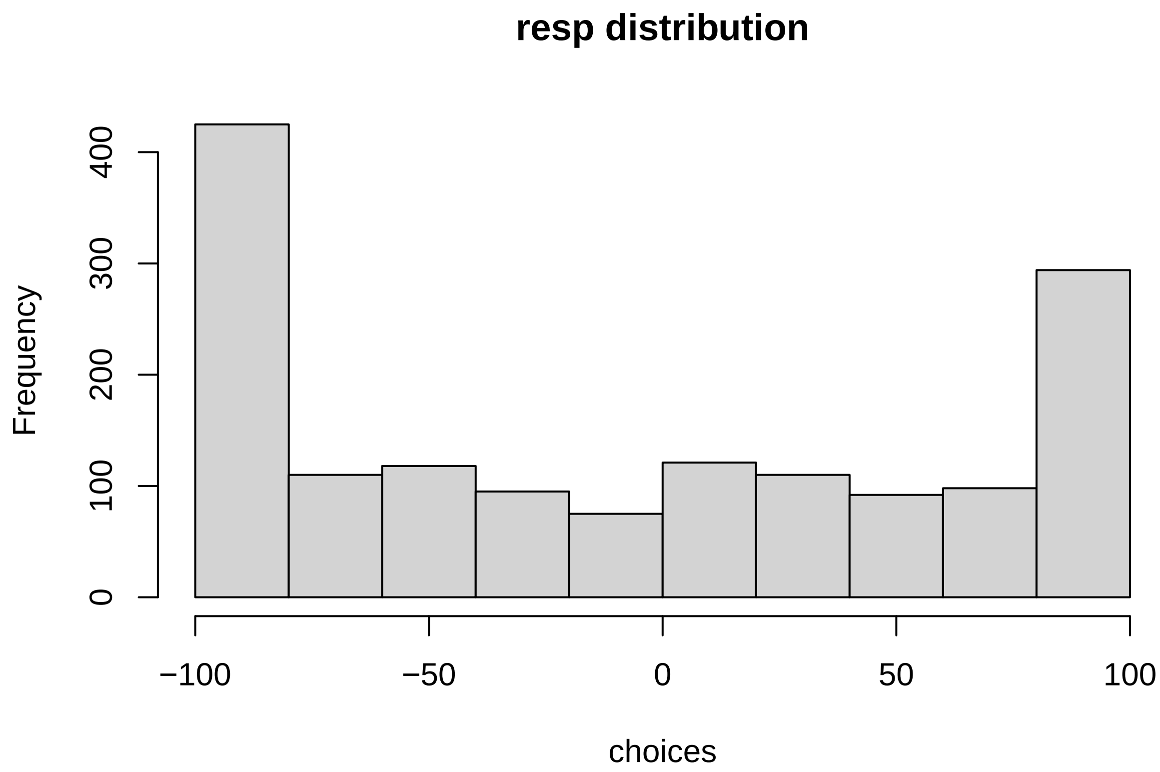



```r
par(mfrow=c(1,1))
```

Resp is coded as factor, need to correct this:

```r
as.numeric(levels(conjudge$resp))[conjudge$resp]-> conjudge$resp
```

```r
hist(conjudge$resp, main = 'resp distribution', xlab = 'choices')
```




Ok, here we don't have right or wrong answers, but we are more interested in take a look how the participants rated the fribble label association:

```
aggregate(resp ~ category, data = conjudge, FUN = mean)
```

```
##   category      resp
## 1        1 -12.52183
## 2        2  -5.50000
## 3        3 -10.09728
```

Let's clean the global environment:

```
rm(n_bins, rt_range, problematicPeople, frequency, dumbPeople, break_seq, task, temp, timeslice_range, p
```

## Bayes factor calculation with GLMMs

### Estimates of the betas from the FLO paper

```
#means
highfreq_mean<- mean(88, 98)
lowfreq_mean <- mean(38, 78)
```

```
n <- c(32)

#sd
highfreq_sd <- c(5*sqrt(n))  #Paper has standard errors represented (I guess),
                     #I'm going to transform it back to standard deviations
lowfreq_sd <- c(5*sqrt(n)) #also, they look the same to me from the picture
                           #but low frequency should lead more variability.
```

Main effect of frequency:

```
frequency_beta<- logodds(highfreq_mean) - logodds(lowfreq_mean)
```

Main effect of learning:

```
#mean
LF_mean <- mean(38, 88)
FL_mean <- mean(78, 98)

n <- c(16)

#sd
LF_sd <- c(5*sqrt(n)) #how can be possible that learnings have the same se?
FL_sd <- c(5*sqrt(n))
```

```
learning_beta <- logodds(FL_mean) - logodds(LF_mean)
#positive > higher in the FL
```

Interaction between freq and learning:

Frequency effect (high-low) is greater in the LF than in FL:

```
#(logodds(highfreq_FL)-logodds(lowfreq_FL))- (logodds(highfreq_LF)-logodds(lowfreq_LF))
freqBylearning_beta <- (logodds(98)-logodds(78))- (logodds(88)-logodds(38))*-1
```

### Combine both generalization tasks in one dataset

I'm going to combine both generalization tasks in one single dataset called genTask

```
genTask <- rbind(labelPicture[labelPicture$rt > 100 & !(labelPicture$subjID %in% badsubjs),],
                 pictureLabel[pictureLabel$rt > 100 & !(pictureLabel$subjID %in% badsubjs),])

genTask$frequency <- as.factor(genTask$frequency)
plyr::revalue(genTask$frequency, c("25"="low"))-> genTask$frequency;
plyr::revalue(genTask$frequency, c("75"="high"))-> genTask$frequency;
```

Relevel the variables:

```
genTask$learning = relevel(genTask$learning, ref = "LF")
genTask$frequency = relevel(genTask$frequency, ref = "low")
genTask <- lizCenter(genTask, list("learning" , "frequency", "task"))
```

### The model

```
genTask_model <- glmer(acc ~  frequency.ct*learning.ct + task + (frequency.ct|subjID) ,
         data = genTask,
         family="binomial",
         control=glmerControl(optimizer = "bobyqa"))

adjusted.genTask_model = adjust_intercept_model(genTask_model, chance = log(0.33/(1-0.33)))
round(adjusted.genTask_model,5)
```

```
##                           Estimate Std. Error z value Pr(>|z|)
## (Intercept)                1.29212    0.16620 7.77446  0.00000
## frequency.ct               1.84662    0.27642 6.68049  0.00000
## learning.ct                0.67456    0.31832 2.11912  0.03408
## taskgeneralizationPL       0.00942    0.08848 0.10644  0.91524
## frequency.ct:learning.ct   0.54929    0.54842 1.00158  0.31655
```

Further inspection:

```
genTask_model.emm <- emmeans(genTask_model , ~ frequency.ct * learning.ct )
contrast(genTask_model.emm, "consec",  simple = "each", combine = F, adjust = "bonferroni")
```

```
## $`simple contrasts for frequency.ct`
## learning.ct = -0.532:
##  contrast                                estimate    SE  df z.ratio p.value
##  0.500307314074985 - -0.499692685925015     1.55 0.395 Inf 3.931   0.0001
##
## learning.ct =  0.468:
##  contrast                                estimate    SE  df z.ratio p.value
##  0.500307314074985 - -0.499692685925015     2.10 0.383 Inf 5.490   <.0001
##
## Results are averaged over the levels of: task
## Results are given on the log odds ratio (not the response) scale.
##
## $`simple contrasts for learning.ct`
## frequency.ct = -0.5:
##  contrast                                estimate    SE  df z.ratio p.value
##  0.468039336201598 - -0.531960663798402    0.400 0.383 Inf 1.044   0.2963
##
## frequency.ct =  0.5:
##  contrast                                estimate    SE  df z.ratio p.value
##  0.468039336201598 - -0.531960663798402    0.949 0.454 Inf 2.090   0.0366
##
## Results are averaged over the levels of: task
## Results are given on the log odds ratio (not the response) scale.
```

Okay, with both tasks together the take home message is the following:

- Main effect of frequency, with high frequency having higher accuracy than low frequency in both learnings.
- Main effect of learning, with FL learning having higher accuracy in the high frequency condition.

- No difference between learnings in the low frequency condition.
- No difference between tasks

I'm going to create a table with the estimates:

```
genTask_bf = data.frame(
    condition = c(
                  "frequency by learning",
                  "learning",
                  "frequency",
                  "task"
                  ),

    meandiff = c(
      round(summary(genTask_model)$coefficients["frequency.ct:learning.ct", "Estimate"],3),
       round(summary(genTask_model)$coefficients["learning.ct", "Estimate"],3),
       round(summary(genTask_model)$coefficients["frequency.ct", "Estimate"],3),
       round(summary(genTask_model)$coefficients["taskgeneralizationPL", "Estimate"],3)
       ),

    sd = c(
      round(summary(genTask_model)$coefficients["frequency.ct:learning.ct", "Std. Error"],3),
       round(summary(genTask_model)$coefficients["learning.ct", "Std. Error"],3),
       round(summary(genTask_model)$coefficients["frequency.ct", "Std. Error"],3),
       round(summary(genTask_model)$coefficients["taskgeneralizationPL", "Std. Error"],3)
       )
)

genTask_bf
```

```
##               condition meandiff    sd
## 1 frequency by learning    0.549 0.548
## 2              learning    0.675 0.318
## 3             frequency    1.847 0.276
## 4                  task    0.009 0.088
```

### BF for Frequency:

```
Bf(sd = genTask_bf[genTask_bf$condition=='frequency',]$sd,
   obtained = genTask_bf[genTask_bf$condition=='frequency',]$meandiff,
   uniform = 0,
   sdtheory = highfreq_sd,
   meanoftheory = frequency_beta,
   tail = 1)
```

```
## $LikelihoodTheory
## [1] 0.02820103
##
## $Likelihoodnull
## [1] 2.72547e-10
```

```
##
## $BayesFactor
## [1] 103472175
```

### BF for learning:

```
Bf(sd = genTask_bf[genTask_bf$condition=='learning',]$sd,
   obtained = genTask_bf[genTask_bf$condition=='learning',]$meandiff,
   uniform = 0,
   sdtheory = LF_sd,
   meanoftheory = learning_beta,
   tail = 1)
```

```
## $LikelihoodTheory
## [1] 0.03914723
##
## $Likelihoodnull
## [1] 0.1318569
##
## $BayesFactor
## [1] 0.2968918
```

### BF for the interaction frequency by learning

```
Bf(sd = genTask_bf[genTask_bf$condition=='frequency by learning',]$sd,
   obtained = genTask_bf[genTask_bf$condition=='frequency by learning',]$meandiff,
   uniform = 0,
   sdtheory = LF_sd, #don't know how to compute sd of the interaction
   meanoftheory = freqBylearning_beta,
   tail = 1)
```

```
## $LikelihoodTheory
## [1] 0.03346949
##
## $Likelihoodnull
## [1] 0.4407467
##
## $BayesFactor
## [1] 0.07593815
```

```
rm(speedacc, n, lowfreq_mean, highfreq_mean, lowfreq_sd, highfreq_sd, LF_mean, FL_mean, LF_sd, FL_sd)
```