Sample size estimation for an effect size of interest in a GLMM design

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Psycholinguistic experiment analysis and design

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Section 1

Data and setup

Setup

Set seed and load packages.

```
set.seed(2022)

library(tidyr);
library(dplyr);
library(ggplot2);
library(simr)
```

Create a dataset

- A dataset from a hypothetical experiment
- Let's assume this dataset is a real one collected from a pilot study.

The dataset

- Within group design, with n=26
- 2 conditions:
  - Noise: Mild and Severe
  - Cloze (=predictability): High and Low
- 10 items in a repeated measures design
- High and Low cloze sentences are embedded in Mild and Severe background noise.
- 10items * 4conditions = 40 trials for each of the 26 participants.

The dataset

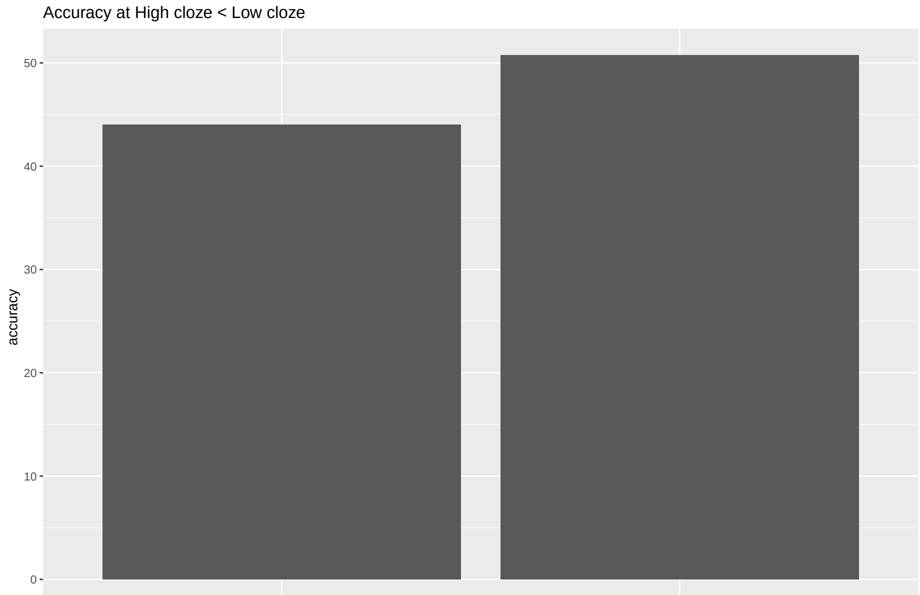
```r
dat <- expand_grid(
  participants = paste(letters, 1:26, sep = '_'),
  noise = c('mild', 'severe'),
  cloze = c('high', 'low'),
  item = paste('item', 1:10, sep = '_'))
dat$acc <- sample(c(0,1), nrow(dat), replace = T)

# Assign class to the variables of interest:
dat$noise <- as.factor(dat$noise)
dat$cloze <- as.factor(dat$cloze)
dat$acc <- as.integer(dat$acc)
```

The dataset

- Note that the experimental conditions are just labels.
- Participants' response accuracy in High cloze sentences does not necessarily have to be higher than Low cloze sentences.
    - Same thing for the noise condition (Severe vs. Mild)

Data summary



Data summary

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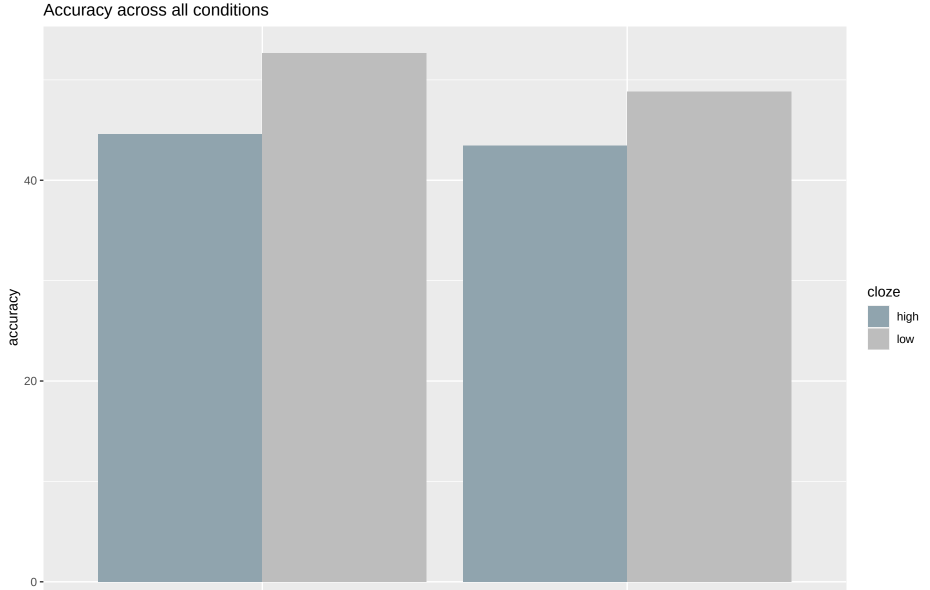

Section 2

Model

Assign contrast

- Treatment contrasts for both *Cloze* and *Noise*

```
contrasts(dat$cloze) <- contr.treatment(2) # High cloze is the
contrasts(dat$noise) <- contr.treatment(2) # Mild noise is the
```

- High cloze, Mild noise conditions in the Intercept

Run a GLMM

- An intercept-only model, with all the main effects and interaction in the fixed effects term.

```
m0 <- glmer(acc ~ 1 + (cloze + noise + cloze:noise) +
                   (1 | participants) + (1 | item),
                  data=dat, family = "binomial",
                  control = glmerControl(calc.derivs = FALSE,
                                         optimizer="bobyqa",
                                         optCtrl = list(maxfun=
                  nAGQ = 0, na.action = na.exclude)
```

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```

- Is this an appropriate model for a repeated measures design?

Model summary

```
summary(m0)$coef
```

```
##                 Estimate Std. Error    z value   Pr(>|z|)
## (Intercept)   -0.21710136  0.1384937 -1.5675898 0.11697690
## cloze2         0.32538206  0.1764229  1.8443298 0.06513509
## noise2        -0.04701666  0.1770520 -0.2655528 0.79058366
## cloze2:noise2 -0.10759011  0.2495983 -0.4310531 0.66642975
```

Remember that High cloze and Mild noise conditions are the reference levels.

Observed effect size

- Interest: Noise condition, i.e., `noise2`

```
fixef(m0)[3] #fixef(m0)['noise2']
```

```
##      noise2
## -0.04701666
```

- The accuracy at Severe noise is lower than at Mild noise, although statistically not significant.

Expected effect size

- Say, we expect the main effect of noise to be 0.05.
- Then, we assign this **effect size of interest** to the model.

```
fixef(m0)['noise2'] <- 0.05 #changed from -0.04701666 to 0.05

# If I assume the effect size will not change in the "real dat
# `fixef(m0)['noise2'] <- fixef(m0)['noise2']` instead.
```

Section 3

Power analyses

Increase sample size

- We want to find out what the power is when the sample size is increased up to a certain number, e.g., n=160.

```
N_tar_grid     <- seq(32, 160, by = 32) # 32, 64, 96, 128, 160
# A vector of five which we'll use later

fit_ext_simr0  <- simr::extend(m0, #increases sample size for
                               along = "participants",
                               n = max(N_tar_grid)
                               )
```

- `nrow(getData(fit_ext_simr0))` = 6400
- `nrow(getData(m0))` = 1040

Power analysis

- To visualize the power at different sample sizes
- Power analyses from the existing model with the extended data:

```
B_boot <- 100 # number of boot repetitions within one experime
# recommended: at least 1000 simulations

noise_power0 <- simr::powerSim(fit_ext_simr0,
                               nsim = B_boot,
                               progress = TRUE,
                               test = fixed('noise2', 'z'))
```

- What is and why z test?

Power analysis

```
noise_power0
```

```
## Power for predictor 'noise2', (95% confidence interval):
##        5.00% ( 1.64, 11.28)
##
## Test: z-test
##       Effect size for noise2 is 0.050
##
## Based on 100 simulations, (0 warnings, 0 errors)
## alpha = 0.05, nrow = 6400
##
## Time elapsed: 0 h 1 m 8 s
```

- The power to reject the null hypothesis is about 5%.
- Note that this power analysis was performed at the sample size of 160.

Power analysis and power curve

- Estimate power across a pre-specified range of sample sizes.
- Check if any of the pre-specified sample sizes provides 80% power for the effect size of interest.

```
noise_powercurve0 <- simr::powerCurve(fit_ext_simr0,
                                      along = 'participants',
                                      nsim = B_boot,
                                      breaks = N_tar_grid, #seq(32, 160,
                                      progress = TRUE,
                                      test = fixed('noise2', 'z'))
```

Power curve

- The power for `noise` at different pre-specified sample sizes:

```
noise_powercurve0
```

```
## Power for predictor 'noise2', (95% confidence interval),
## by largest value of participants:
##      127:  3.00% ( 0.62,  8.52) - 1280 rows
##      156:  5.00% ( 1.64, 11.28) - 2560 rows
##       40:  7.00% ( 2.86, 13.89) - 3840 rows
##        7:  8.00% ( 3.52, 15.16) - 5120 rows
##       99: 13.00% ( 7.11, 21.20) - 6400 rows
##
## Time elapsed: 0 h 2 m 36 s
```

Power curve

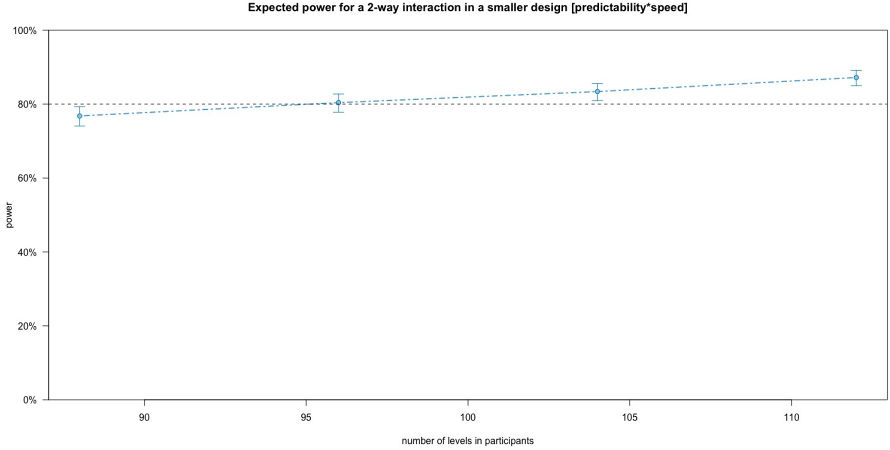

Figure 1: A typical powercurve.

Problems with the analysis

- Problem 1: None of the pre-specified sample sizes have $>$80% power
- Problem 2: Power for n=99 $>$ Power for n=127

Sources of the problems

- Not enough simulations: Some sets of simulations might be poor fit

Test slide

- Eat eggs

Test slide

- Eat eggs
- Drink coffee