Simulated Grant Data

Overview

The code below attempts to create a simulated dataset for the purposes of evaluating how factors such as the level of expertise (high, medium, low, not enough) and role (reviewer, panelist) might impact overall scores.

The unit of observation is the application and basic structure attempts to mimic the multilevel nature of the review process for the CIHR Project Grant competitions. There are roughly 50 CIHR Committees, and each committee has around 25 or so members. In practice the number of total applications may vary quite a lot across committees (e.g., up to 50 for PH1 or PH2 when I was SO); however since we are focused on the evaluation of overall scores *among those proposals discussed* (i.e., excluding those streamlined), this is likely closer to 15 or so proposals per committee (again, my reference is PH committees).

In the code below we specify 50 committees, 15 discussed applications per committee, and 24 members per committee.

The code below is annotated with some simple coefficients for reviewer status and expertise (no interaction).

First, load the packages needed for this setup and analysis

```
# list of packages needed
pkgs <- c('here', 'tidyverse', 'faux', 'modelsummary',
  'fixest', 'tinytable', 'marginaleffects',
  'truncnorm', 'lme4')

# install any needed packages
# install.packages(pkgs)

# load all packages at once
lapply(pkgs, library, character.only=TRUE)
```

Now we set up simple parameters and multilevel structure for the simulated data. For simplicity we take 50 committees and 24 members per committee, though in practice it seems likely that this would vary across committees. Note that since we are focused on those applications that are not streamlined and make it to discussion, we limit the number of applications to 15 per committee (again, this would probably vary across committees). In addition, given this is restricted to the discussion phase the distribution of the overall score is truncated. CIHR places an upper limit of 4.9 for the highest ranking and in many cases a lower level of 3.5 is used (though not the only criteria) to draw the line below which applications are streamlined.

```r
# set seed for reproducibility
set.seed(4875)

# define parameters
cmte_n = 50       # number of committees
app_n = 15        # number of discussed applications
mem_n = 24        # number of committee members
b0 = 4.1          # intercept for average score
b1 = 0.2          # fixed effect of panelist vs. reviewer
b2 = -0.1         # fixed effect of high expertise
b3 = 0.1          # fixed effect of low expertise
b4 = 0.2          # fixed effect of no expertise
u0c_sd = 0.1      # random intercept SD for committee
u0m_sd = 0.2      # random intercept SD for members
u0a_sd = 0.2      # random intercept SD for applications
sigma_sd = 0.2    # error SD for overall scores
score_min = 3.5   # lower bound for score
score_max = 4.9   # upper bound for score

# set up data structure
data <- add_random(committee = cmte_n,
  application = app_n, member = mem_n) |>

  # recode values for committee, application, and member
  add_between("committee",
    cmte = sprintf("%02d", 1:cmte_n)) |>
  add_between("application",
    app = 1:app_n) |>
  add_between("member",
    memno = sprintf("%02d", 1:mem_n)) |>

  # create unique ID for each committee member
  mutate(cid = paste0(cmte, "_", memno)) |>

  # assign reviewers uniquely within each application
  group_by(cmte, app) |>
  mutate(
    job = sample(c(rep("reviewer", 3),
      rep("panelist", 21))),
    # add expertise for each member
    exp = sample(c(rep("high", 6),
      rep("med", 10), rep("low", 4),
      rep("none", 4)))) |>
  ungroup() |>
```

```r
  # add indicators for reviewer, expertise
  mutate(
    panelist = if_else(job == "panelist", 1, 0),
    exp_high = if_else(exp == "high", 1, 0),
    exp_low = if_else(exp == "low", 1, 0),
    exp_none = if_else(exp == "none", 1, 0)
  ) |>

  # add random effects
  add_ranef("cmte", u0c = u0c_sd) |>
  add_ranef("member", u0m = u0m_sd) |>
  add_ranef("application", u0a = u0a_sd) |>
  add_ranef(sigma = sigma_sd) |>

  # Compute score using a truncated normal distribution
  mutate(
    score = rtruncnorm(n(), a = score_min, b = score_max,
      mean = b0 + u0c + u0m + u0a +
        (b1 * panelist) + (b2 * exp_high) +
        (b3 * exp_low) + (b4 * exp_none),
      sd = sigma_sd)
  ) |>

  # drop intermediate variables
  select(-committee, -application, -member,
         -u0c, -u0m, -u0a, -sigma)
```

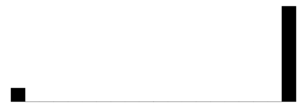
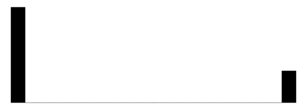
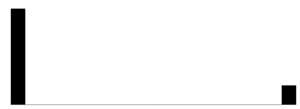
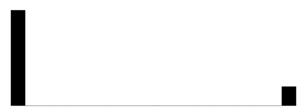
Here is a glimpse of the data structure:

```r
tt(head(data), digits = 2) |>
  style_tt(fontsize = 0.8)
```

cmte	app	memno	cid	job	exp	panelist	exp_high	exp_low	exp_none	score
01	1	01	01_01	panelist	none	1	0	0	1	4.4
01	1	02	01_02	panelist	med	1	0	0	0	4.5
01	1	03	01_03	panelist	med	1	0	0	0	3.9
01	1	04	01_04	reviewer	none	0	0	0	1	3.9
01	1	05	01_05	panelist	high	1	1	0	0	4
01	1	06	01_06	panelist	low	1	0	1	0	4.4

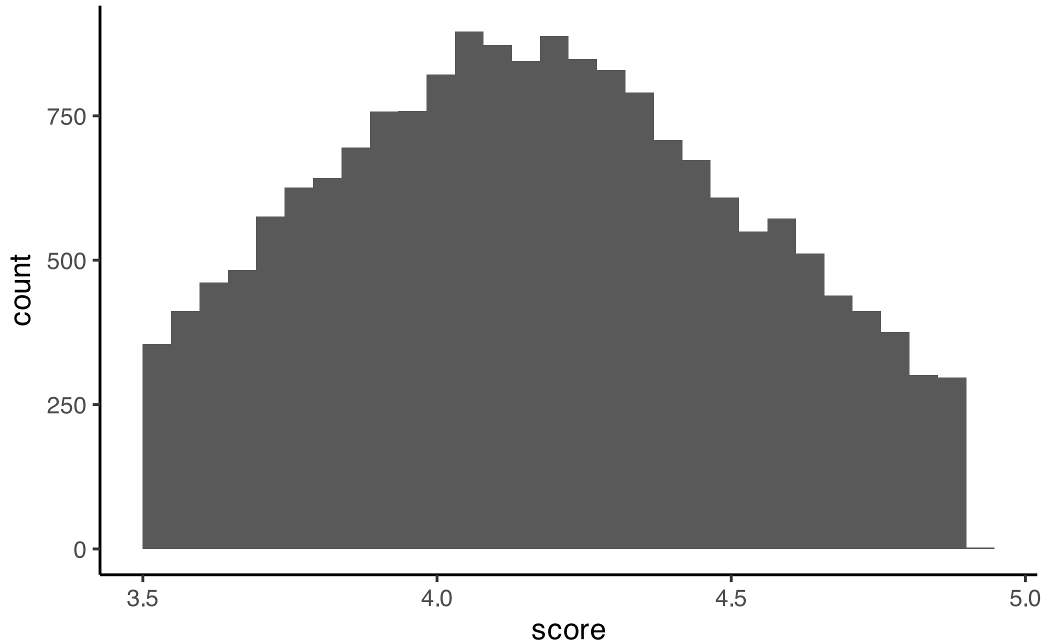
Some basic descriptive statistics for each of the variables:

```r
datasummary_skim(data, type = "numeric")
```

	Unique	Missing Pct.	Mean	SD	Min	Median	Max	Histogram
app	15	0	8.0	4.3	1.0	8.0	15.0	
panelist	2	0	0.9	0.3	0.0	1.0	1.0	
exp_high	2	0	0.2	0.4	0.0	0.0	1.0	
exp_low	2	0	0.2	0.4	0.0	0.0	1.0	
exp_none	2	0	0.2	0.4	0.0	0.0	1.0	
score	18000	0	4.2	0.3	3.5	4.2	4.9	

And a simple histogram of the distribution of overall scores:

```
ggplot(data, aes(x = score)) + geom_histogram() +
         theme_classic()
```



A simple set of models with random effects for committee, member, and application, and fixed effects for whether or not the score comes from a panelist and various levels of expertise (should probably be estimated by interval regression or some other way of accounting for the truncated distribution of the outcome, but later):

```
# empty
m0 <- lmer(score ~ 1 + (1 | cmte) + (1 | memno) +
  (1 | app), data = data)

# add reviewer
m1 <- lmer(score ~ 1 + factor(job) + (1 | cmte) +
  (1 | memno) + (1 | app), data = data)

# add expertise
m2 <- lmer(score ~ 1 + factor(job) + factor(exp) +
  (1 | cmte) + (1 | memno) + (1 | app),
  data = data)

ms <- modelsummary(list("Empty" = m0,
  "+ Reviewer" = m1, "+ Expertise" = m2),
  gof_omit = 'DF|Deviance|R2|AIC|BIC|RMSE',
  escape = TRUE)

tt(ms@table_dataframe, digits = 3) |>
  style_tt(fontsize = 0.5)
```

	Empty	+ Reviewer	+ Expertise
(Intercept)	4.172	4.194	4.087
	(0.064)	(0.064)	(0.064)
factor(job)reviewer		-0.171	-0.170
		(0.005)	(0.004)
factor(exp)low			0.171
			(0.004)
factor(exp)med			0.083
			(0.004)
factor(exp)none			0.259
			(0.004)
SD (Intercept cmte)	0.078	0.078	0.078
SD (Intercept memno)	0.190	0.189	0.188
SD (Intercept app)	0.191	0.191	0.191
SD (Observations)	0.216	0.208	0.189
Num.Obs.	18000	18000	18000
ICC	0.6	0.6	0.7

In the above simulation these effects are simply additive, but it is possible to generate predicted scores for applications that happen to have specific characteristics. For example, we can contrast the predicted scores for a panelist with "Not enough" expertise with that of a reviewer with high expertise:

```
p1 <- predictions(m2,
  newdata = datagrid(job = unique, exp = unique))

p1 |> select(job, exp, estimate, conf.low, conf.high) |>
  tt(digits = 3) |>
  style_tt(fontsize = 1)
```

job	exp	estimate	conf.low	conf.high
panelist	none	4.14	4.02	4.27
panelist	med	3.97	3.84	4.09
panelist	high	3.88	3.76	4.01
panelist	low	4.05	3.93	4.18
reviewer	none	3.97	3.85	4.1
reviewer	med	3.8	3.67	3.92
reviewer	high	3.71	3.59	3.84
reviewer	low	3.88	3.76	4.01

This toy example leads to average predictions of 4.1 for a panelist with “Not enough” experience vs. 3.7 for a reviewer with a “high” level of expertise. To the extent that committees vary in their composition of expertise, this could have some impact on overall scores.

Potential extensions

In large part the simplified dataset above only allows for basic questions regarding how much, for example, expertise and reviewer status may affect the overall score. More interesting questions could be asked if additional fields are available at different levels of the data.

Application level

Additional data on initial reviewer scores, consensus score, keywords or domain of inquiry, re-submission status, no. of investigators, funding requested.

Reviewer level

Data on reviewer gender, experience, past funding success, conflicts of interest

Applicant level

Data (respecting confidentiality) on gender, career stage, age, scientific productivity, prior funding success, would allow for the investigation