Analyzing NAEP and TIMSS Data with Direct Estimation using the R packages EdSurvey and Dire

Presenters: Paul Bailey, Ting Zhang, Michael Lee & Sinan Yavuz

April 2022

Workshop Goal

Provide participants with an overview of the plausible values and direct estimation methods used to analyze national and international large-scale assessment data using the R package `EdSurvey` and `Dire`.

Follow along in edsurvey_part2_Script.R

Outline of EdSurvey Workshop - Part 2

1. Descriptive statistics
2. Hands-on practice
3. Direct estimation with EdSurvey and Dire
4. Hands-on practice

Data Processing

- First, load the `EdSurvey` package and read in the data

```
# to load the package
library(EdSurvey)
library(Dire)
```

NAEP Primer:

```
sdf <- readNAEP(system.file("extdata/data", "M36NT2PM.dat",
                                package = "NAEPprimer"))
```

Summary statistics

NAEP
NATIONAL ASSESSMENT OF EDUCATIONAL PROGRESS

Summary statistics

`summary2()` produces both weighted and unweighted descriptive statistics for a variable. `summary2()` takes four following arguments in order:

- `data` : an `EdSurvey` object.
- `variable` : name of the variable you want to produce statistics on.
- `weightVar` : name of the weight variable; or `NULL` if users want to produce unweighted statistics.
- `omittedLevels` : if `TRUE`, the function will remove omitted levels for the specified variable before producing descriptive statistics. If `FALSE`, the function will include omitted levels in the output statistics.

Summary statistics

For a continuous variable (i.e., composite Math score):

- For NAEP data and other datasets that have default weight variable, `summary2` produces weighted statistics by default. If specified, `variable` is a plausible value and weight option is selected, `summary2` statistics account for both plausible value pooling and weighting.

```
summary2(sdf, "composite")
```

```
## Estimates are weighted using the weight variable 'origwt'
##    Variable     N Weighted N   Min.  1st Qu.   Median     Mean  3rd Qu.    Max.      SD NA's Zero weights
## 1 composite 16915   16932.46 126.11 251.9626 277.4784 275.8892 301.1827 404.184 36.5713    0            0
```

Summary statistics

For a continuous variable (i.e., composite Math score):

- By specifying `weightVar = NULL`, the function prints out unweighted descriptive statistics for `variable`, or each plausible value if `variable` is a plausible value name.

```
summary2(sdf, "composite", weightVar = NULL)
```

```
## Estimates are not weighted.
##   Variable     N   Min.  1st Qu. Median     Mean  3rd Qu.   Max.       SD NA's
## 1   mrpcm1 16915 130.53 252.0600 277.33 275.8606 300.7200 410.80 35.89864    0
## 2   mrpcm2 16915 124.16 252.2100 277.33 275.6399 300.6900 408.58 36.08483    0
## 3   mrpcm3 16915 115.09 252.0017 277.19 275.6570 300.5600 398.17 36.09278    0
## 4   mrpcm4 16915 137.19 252.4717 277.44 275.7451 300.5767 407.41 35.91078    0
## 5   mrpcm5 16915 123.58 252.4900 277.16 275.6965 300.5000 395.96 36.10905    0
```

Summary statistics

For a categorical variable (i.e., frequency of students talking about studies at home):

- By default, `omittedLevels` is set to `FALSE`. That is, the function includes omitted levels of the variable `b017451` in the output statistics.

```
summary2(sdf, "b017451")
```

```
## Estimates are weighted using the weight variable 'origwt'
##                 b017451    N Weighted N Weighted Percent Weighted Percent SE
## 1 Never or hardly ever 3837  3952.4529      23.34245648           0.4318975
## 2 Once every few weeks 3147  3190.8945      18.84483329           0.3740648
## 3    About once a week 2853  2937.7148      17.34960077           0.3414566
## 4  2 or 3 times a week 3362  3425.8950      20.23270282           0.3156289
## 5            Every day 3132  3223.8074      19.03921080           0.4442216
## 6              Omitted  575   194.3312       1.14768416           0.1272462
## 7             Multiple    9     7.3676       0.04351168           0.0191187
```

Summary statistics

For a categorical variable (i.e., frequency of students talking about studies at home):

- By specifying `omittedLevels = TRUE`, the function removes omitted levels out of the output statistics.

```
summary2(sdf, "b017451", omittedLevels = TRUE)
```

```
## Estimates are weighted using the weight variable 'origwt'
##                b017451    N Weighted N Weighted Percent Weighted Percent SE
## 1 Never or hardly ever 3837   3952.453         23.62386           0.4367548
## 2 Once every few weeks 3147   3190.894         19.07202           0.3749868
## 3    About once a week 2853   2937.715         17.55876           0.3486008
## 4   2 or 3 times a week 3362   3425.895         20.47662           0.3196719
## 5            Every day 3132   3223.807         19.26874           0.4467063
```

Cross tabulation

`edsurveyTable()`: creates a summary table of outcome and categorical variables. There are 3 important arguments as followed:

- `formula`: typically written as `a ~ b + c`, in which:
  - `a`: a continuous variable (optional) that the function will return weighted mean on.
  - `b` and `c`: categorical variable(s) that the function will run cross-tabulation on; multiple crosstab categorical variables can be separated using `+` symbol.
- `data`: an `EdSurvey` object
- `pctAggregationLevel`: a numeric value (i.e., 0, 1, 2) that indicates the level of aggregation in the cross-tabulation result's percentage column.

Cross tabulation

- Summary table of NAEP composite mathematics performance scale scores (`composite`) of 8th grade students by two student factors:
  - `dsex`: gender
  - `b017451`: frequency of talk about studies at home

```
es1 <- edsurveyTable(composite ~ dsex + b017451, data = sdf)
```

- `pctAggregationLevel` is by default set to `NULL` (or `1`). That is, the `PCT` column adds up to 100 within each level of the first categorical variable `dsex`.

dsex	b017451	N	WTD_N	PCT	SE(PCT)	MEAN	SE(MEAN)
Male	Never or hardly ever	2350	2434.844	29.00978	0.6959418	270.8243	1.057078
Male	Once every few weeks	1603	1638.745	19.52472	0.5020657	275.0807	1.305922
Male	About once a week	1384	1423.312	16.95795	0.5057265	281.5612	1.409587
Male	2 or 3 times a week	1535	1563.393	18.62694	0.4811497	284.9066	1.546072

Cross tabulation

- By specifying `pctAggregationLevel = 0`, the `PCT` column adds up to 100 across the entire sample.

```
es2 <- edsurveyTable(composite ~ dsex + b017451, data = sdf, pctAggr
```

dsex	b017451	N	WTD_N	PCT	SE(PCT)	MEAN	SE(MEAN)
Male	Never or hardly ever	2350	2434.844	14.553095	0.3738531	270.8243	1.057078
Male	Once every few weeks	1603	1638.745	9.794803	0.2651368	275.0807	1.305922
Male	About once a week	1384	1423.312	8.507154	0.2770233	281.5612	1.409587
Male	2 or 3 times a week	1535	1563.393	9.344421	0.2670298	284.9066	1.546072
Male	Every day	1291	1332.890	7.966700	0.3000579	277.2597	1.795784
Female	Never or hardly ever	1487	1517.609	9.070768	0.2984443	266.7897	1.519020
Female	Once every few weeks	1544	1552.149	9.277216	0.2498498	271.2255	1.205528
Female	About once a week	1469	1514.403	9.051606	0.2899668	278.7502	1.719778
Female	2 or 3 times a week	1827	1862.502	11.132198	0.2552321	282.7765	1.404107
Female	Every day	1841	1890.918	11.302039	0.3497982	275.4628	1.219439

Cross tabulation

- Related Documentation - EdSurvey-LaTeXtables.pdf, Chap 5.4.1, EdSurvey Book

Self-Reflection - edsurveyTable

Ask yourself: Use EdSurvey functions to create a summary table using `edsurveyTable` with these parameters:

- overall math performance across subscales (`composite`)
- variable that has to do with IEP status
- variable that has to do with number of books at home

Self-Reflection - edsurveyTable

Scenario Result:

```
edexercise <- edsurveyTable(composite ~ iep + b013801,
                            weightVar = 'origwt', data = sdf)
edexercise
```

```
##
## Formula: composite ~ iep + b013801
##
## Plausible values: 5
## jrrIMax: 1
## Weight variable: 'origwt'
## Variance method: jackknife
## JK replicates: 62
## full data n: 17606
## n used: 16351
##
##
## Summary Table:
##  iep b013801    N      WTD_N      PCT   SE(PCT)     MEAN  SE(MEAN)
##  Yes    0-10  304   297.1972 17.33406 1.0388812 226.1623 2.3075125
##  Yes   11-25  430   429.6252 25.05794 1.4034976 231.8103 2.3796081
##  Yes  26-100  517   530.9539 30.96795 1.5297784 249.2306 2.4682667
##  Yes    >100  457   456.7507 26.64004 1.6556494 257.6787 2.8205193
##   No    0-10 1720  1890.3037 12.56502 0.4765198 257.6975 1.2861579
##   No   11-25 2936  3170.9954 21.07789 0.5632689 266.0401 0.9908671
##   No  26-100 5330  5350.4978 35.56524 0.6242526 281.5820 0.8305656
##   No    >100 4657  4632.3807 30.79185 0.8511616 296.2606 1.0533164
```

Linear Regression with PVs

NAEP

NATIONAL ASSESSMENT OF EDUCATIONAL PROGRESS

Linear Regression with PVs - lm.sdf()

`lm.sdf()`: fits a linear model formula using sampling weights and a variance estimation method. The format is:

```
myfit <- lm.sdf(formula, data, weightVar, varMethod,
relevels)
```

- `formula`: model to be fit.
- `data`: data frame containing the data to be used in fitting the model.
- `weightVar`: indicates the weight variable to use.
- `varMethod`: the variance estimation method (Jackknife or Taylor series) with the Jackknife as the default.
- `relevels`: is used when the user wants to change the reference level of a categorical variable.

Linear Regression with PVs - lm.sdf()

The resulting object (`myfit` in this case) is a list containing extensive information about the fitted model.

Formula notation is typically written as:

```
Y ~ X1 + X2 + ... + Xk
```

- The `~` separates the response variable on the left from the predictor variables on the right.
- The `+` sign separates the predictor variables.

Regressions with PVs - lm.sdf()

$$\texttt{Composite} = \beta_0 +$$

$$\beta_1 \texttt{Freq. of talk about studies at home} + \epsilon$$

```
lm1 <- lm.sdf(composite ~ dsex + b013801,
              weightVar = 'origwt', data = sdf)
summary(lm1)
```

```
##
## Formula: composite ~ dsex + b013801
##
## Weight variable: 'origwt'
## Variance method: jackknife
## JK replicates: 62
## Plausible values: 5
## jrrIMax: 1
## full data n: 17606
## n used: 16359
##
## Coefficients:
```

Self-Reflection - lm.sdf

Ask yourself: Use EdSurvey functions to perform a regression with multiple predictors using `lm.sdf` using these parameters:

- overall math performance across subscales (`composite`)
- variable that has to do with computers at home
- variable that has to do with language other than English spoken in home

Self-Reflection - lm.sdf

Scenario Result:

```
lmexercise2 <- lm.sdf(composite ~ b017101 + b018201,
                      weightVar = 'origwt', data = sdf)
summary(lmexercise2)
```

```
##
## Formula: composite ~ b017101 + b018201
##
## Weight variable: 'origwt'
## Variance method: jackknife
## JK replicates: 62
## Plausible values: 5
## jrrIMax: 1
## full data n: 17606
## n used: 15884
##
## Coefficients:
##                                  coef      se         t    dof  Pr(>|t|)
## (Intercept)                 281.95112 0.80871 348.64281 43.827 < 2.2e-16 ***
## b017101No                   -22.44306 1.36521 -16.43932 42.935 < 2.2e-16 ***
## b018201Once in a while        0.63672 0.90717   0.70188 61.423    0.4854
## b018201Half the time         -7.32985 1.58448  -4.62604 50.514 2.624e-05 ***
## b018201All or most of time -12.61417 1.27458  -9.89675 29.860 6.121e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared: 0.0658
```

Direct estimation with EdSurvey and Dire

NAEP
NATIONAL ASSESSMENT OF EDUCATIONAL PROGRESS

Direct Estimation with EdSurvey

`mml.sdf`

- The `mml.sdf` function in `EdSurvey` enables marginal maximum likelihood estimation (MML) of linear models for NAEP and TIMMS.
- `mml.sdf` was designed to automate weighting and complex design calculation with simple steps. The direct estimation can be done in `EdSurvey` with a simplified operation via the `mml.sdf` function
- Item parameters, scoring, scaling and weighting information were grabbed from existing NAEP documents, and multiple procedures were streamlined and calculated behind the scene automatically.
- Plausible values (PVs) can be drawing from the latent distribution with `drawPVs`.

Direct Estimation with EdSurvey

`mml.sdf`

- formula: this is the conditioning model
  - dsex: student gender
  - b013801: books in the home
- data: the data set

```
mmlA <- mml.sdf(composite ~ dsex + b013801, data=sdf, weightVar='ori
```

```
## Loading required namespace: doParallel
## Warning: executing %dopar% sequentially: no parallel backend registered
```

```
summary(mmlA)
```

```
## Call:
## mml.sdf(formula = composite ~ dsex + b013801, data = sdf, weightVar = "origwt",
##     multiCore = TRUE, idVar = "ROWID")
## Summary Call:
## summary.mml.sdf(object = mmlA)
##
```

Draw PVs with EdSurvey `drawPVs`

- The `drawPVs` requires two data sources:
  - an `edsurvey.data.frame` (in this case, the primer data `sdf`), and
  - a fit from a call to `mml.sdf` or a `summary` of `mml.sdf` call (i.e., `mmlA` from the example).
- The `npv` argument specifies the number of PVs for the scale.

```
sdf2 <- drawPVs(sdf, mmlA, npv=20L)
```

```
## Warning in (function (data, varnames = NULL, drop = FALSE, dropUnusedLevels = TRUE, : Updating labels on 'm144901' becau
## are multiples of the label 'Correct'.
## Warning in (function (data, varnames = NULL, drop = FALSE, dropUnusedLevels = TRUE, : Updating labels on 'm145101' becau
## are multiples of the label 'Correct'.
## Calculating posterior distribution for construct algebra (1 of 5)
## Calculating posterior distribution for construct data (2 of 5)
## Calculating posterior distribution for construct geometry (3 of 5)
## Calculating posterior distribution for construct measurement (4 of 5)
## Calculating posterior distribution for construct number (5 of 5)
## Calculating posterior correlation between construct algebra and data (1 of 10)
## Calculating posterior correlation between construct algebra and geometry (2 of 10)
```

Use new PVs with EdSurvey `drawPVs`

- The new plausible values variables end with `_dire`
- these can be used to fit a regression with any combination of conditioning variables
- variables must be included in the conditioning model (`mml.sdf` call) for the estimator to be unbiased

```
lm2 <- lm.sdf(composite_dire ~ b013801, data=sdf2)
```

Use new PVs with EdSurvey `drawPVs`

```
summary(lm2)
```

```
##
## Formula: composite_dire ~ b013801
##
## Weight variable: 'origwt'
## Variance method: jackknife
## JK replicates: 62
## Plausible values: 20
## jrrIMax: 1
## full data n: 17606
## n used: 16359
##
## Coefficients:
##                    coef       se        t    dof  Pr(>|t|)
## (Intercept)    251.6316   1.2829 196.1436 32.878 < 2.2e-16 ***
## b01380111-25    10.7207   1.5740   6.8111 40.836 3.107e-08 ***
## b01380126-100   27.2498   1.4467  18.8354 32.890 < 2.2e-16 ***
## b013801>100     42.2177   1.5198  27.7785 67.294 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared: 0.1914
```

Use new PVs with EdSurvey `drawPVs`

- Variables not included in the conditioning model (`mml.sdf` call) will have biased estimates
- this includes interaction terms

```
lm1a <- lm.sdf(composite ~ b018201, data=sdf2)
summary(lm1a)$coefmat
```

```
##                                   coef        se           t      dof     Pr(>|t|)
## (Intercept)                 279.3510325 0.9015424 309.8589995 32.41016 0.000000e+00
## b018201Once in a while        0.7718548 0.9499216   0.8125458 60.62978 4.196576e-01
## b018201Half the time         -9.0098638 1.6034921  -5.6189012 37.47070 1.981582e-06
## b018201All or most of time -14.5362514 1.3103503 -11.0934085 27.26864 1.294259e-11
```

```
lm1b <- lm.sdf(composite_dire ~ b018201, data=sdf2)
summary(lm1b)$coefmat
```

```
##                                  coef        se          t      dof     Pr(>|t|)
## (Intercept)                 278.463321 0.6742498 412.997246 43.57473 0.000000e+00
## b018201Once in a while        1.360532 1.0774220   1.262766 61.48771 2.114412e-01
## b018201Half the time         -6.630013 1.6339818  -4.057581 50.63910 1.716528e-04
## b018201All or most of time -10.439672 1.2572012  -8.303899 55.75191 2.531460e-11
```

Self-Reflection - `mml.sdf`

Ask yourself: Use EdSurvey functions to perform Direct Estimation with multiple predictors using `mml.sdf` using these parameters:

- algebra math performance across subscales (composite)
- variable that has to do with attendance/absence
- variable(s) that has to do with effort on the test

Self-Reflection - `mml.sdf`

Scenario Result:

```
mmlExercise1 <- mml.sdf(algebra ~ b018101 + m815401 + m815501, data =
```

```
## Warning in mml.sdf(algebra ~ b018101 + m815401 + m815501, data = sdf): These items were in the assessment, but not in yo
## m0732cl, m073601, m092401, m092601, m141301, m141901, m012231, m012431, m013331, m019201, m020901, m021001, m051701, m05
## m067001, m073001, m073101, m073301, m091901, m092201, m140401, m140501, m140601, m140701, m140801, m140901, m141001, m14
## m141201, m141401, m141501, m141601, m141701, and m141801
```

```
summary(mmlExercise1)
```

```
## Call:
## mml.sdf(formula = algebra ~ b018101 + m815401 + m815501, data = sdf)
## Summary Call:
## summary.mml.sdf(object = mmlExercise1)
##
## Summary:
##                            Estimate   StdErr  t.value
## (Intercept)                289.6188   1.6197 178.8092
## b0181011-2 days             -6.6006   1.1096  -5.9488
## b0181013-4 days            -15.9040   1.5078 -10.5478
## b0181015-10 days           -19.4088   1.7553 -11.0572
## b018101More than 10 days   -35.7046   3.3311 -10.7186
## b018101Omitted             -11.2818   5.3003  -2.1285
## b018101Multiple            -23.5953  12.7330  -1.8531
```

Data Synthesis example

NATIONAL ASSESSMENT OF EDUCATIONAL PROGRESS

Direct Estimation with Dire

The `Dire` package enables MML linear model and PVs generation for assessment data.

It is flexible for data linking or data frame expanding (e.g., adding Principle Component variables).

Multiple steps required:

- Process the data, link datasets if needed
- Prepare necessary arguments for item, location, scale and weight parameters
- Run MML regression
- Summary of the fitted results with the Taylor series method
- Draw PVs

Data Processing and Exploration

The `NAEPDataSimulation` package includes a simulated NAEP-like dataset. This dataset was generated by using the NAEP 2015 Mathematics 8 grade item parameters and block design.

```
require(NCESDatalike)
```

```
## Loading required package: NCESDatalike
```

```
#Simulated NAEP-like
sNl <- readNAEP(system.file("extdata/data", "M46NT2PM.dat",
                            package = "NCESDatalike"))
cd <- showCodebook(sNl)
```

Data Linking

- We will merge a data from The US Census Bureau and the simulated NAEP-like data.
- However, the possibilities are endless as long as there is a common variable to combine datasets from different resources.
- From the selection of data provided by The US Census Bureau we choose the following variable from American Community Survey (ACS) 5-Year Data (2009-2020) dataset:

B06011_001E: Median income in the past 12 months (in 2019 inflation-adjusted dollars) by place of birth in the United States

- The dataset and all other variables can be found here. https://api.census.gov/data/2019/acs/acs5/variables.html

Data Linking - Download the external dataset

Because the dataset is publicly available it can be directly downloaded as follows:

```
url="https://api.census.gov/data/2019/acs/acs5?get=NAME,B06011_001E&
temp <- tempfile()
download.file(url , temp)
AcsDt <- read.table(temp, sep=",",header = TRUE)
unlink(temp)
head(AcsDt)
```

```
##        X..NAME B06011_001E state zip.code.tabulation.area.  X
## 1 [ZCTA5 01001       36257    25                    01001] NA
## 2 [ZCTA5 01002       17716    25                    01002] NA
## 3 [ZCTA5 01003        4054    25                    01003] NA
## 4 [ZCTA5 01005       39944    25                    01005] NA
## 5 [ZCTA5 01007       43144    25                    01007] NA
## 6 [ZCTA5 01008       41458    25                    01008] NA
```

Data Linking - Clean up the ACS data

- Before merging, we need to clean the brackets and replace the missing values with `NA`. Additionally, we will divide the median income variable by 10,000 for quicker convergence and more readible coefficients.

```
#remove the opening bracket on the first column
AcsDt[,1] <- gsub(pattern="\\[", replacement="", x= AcsDt[,1])
#remove the last empty column
AcsDt$X <- NULL
#remove the bracket from the last column
AcsDt[,ncol(AcsDt)] <- gsub(pattern="\\]",
                            replacement="", x= AcsDt[,ncol(AcsDt)])
AcsDt$B06011_001E[AcsDt$B06011_001E==-666666666] <- NA
AcsDt$B06011_001E <- as.numeric(AcsDt$B06011_001E)
```

```
## Warning: NAs introduced by coercion
```

```
AcsDt$B06011_001E_10K <- AcsDt$B06011_001E/10000
```

Data Linking - The ACS data

- Here is the cleaned ACS data

```
head(AcsDt)
```

```
##       X..NAME B06011_001E state zip.code.tabulation.area. B06011_001E_10K
## 1 ZCTA5 01001       36257    25                     01001          3.6257
## 2 ZCTA5 01002       17716    25                     01002          1.7716
## 3 ZCTA5 01003        4054    25                     01003          0.4054
## 4 ZCTA5 01005       39944    25                     01005          3.9944
## 5 ZCTA5 01007       43144    25                     01007          4.3144
## 6 ZCTA5 01008       41458    25                     01008          4.1458
```

```
tail(AcsDt)
```

```
##           X..NAME B06011_001E state zip.code.tabulation.area. B06011_001E_10K
## 33115 ZCTA5 00736          NA    72                     00736              NA
## 33116 ZCTA5 00907          NA    72                     00907              NA
## 33117 ZCTA5 00786          NA    72                     00786              NA
## 33118 ZCTA5 00694          NA    72                     00694              NA
## 33119 ZCTA5 00631          NA    72                     00631              NA
## 33120 ZCTA5 00926          NA    72                     00926              NA
```

Data Linking - Clean up and merge

- We will merge this data with the simulated data by using the zip code variable.

```
items <- cd$variableName[grep("item m", cd$Labels)]
simdf <- EdSurvey::getData(sNl, varnames = c("idvar","dsex", "pared"
                                             "repgrp1", "jkunit", "o
                                             items), omittedLevels =
linkedData <- merge(simdf, AcsDt, by.x = "zip",
                    by.y = "zip.code.tabulation.area.", all.x = TRUE
linkAtt <- rebindAttributes(linkedData, sNl)
```

MML Model - `mml`

- `mml` function can estimate a linear model via marginal maximum likelihood.

```
fit <- mml.sdf(composite ~ B06011_001E_10K + dsex + pared,
               data = linkAtt, weightVar='origwt', idVar="idvar")
```

```
## Warning in mml.sdf(composite ~ B06011_001E_10K + dsex + pared, data = linkAtt, : m152602, m2372cl, m3498cl did not have
## parameters for the max score and will be taken out of analysis.
## Warning in mml.sdf(composite ~ B06011_001E_10K + dsex + pared, data = linkAtt, : Removing 350 rows with NAs from analysi
```

MML Model - Summary of the model

```
summary(fit)
```

```
## Warning in getVarTaylor(object = obj, H_B_prime = H_B_prime0[block[[i]], : Of the 25 strata, 1 strata have only one PSU. All
## strata with only one PSU are excluded from variance estimation. See the "singletonFix" argument for other options.

## Warning in getVarTaylor(object = obj, H_B_prime = H_B_prime0[block[[i]], : Of the 25 strata, 1 strata have only one PSU. All
## strata with only one PSU are excluded from variance estimation. See the "singletonFix" argument for other options.

## Warning in getVarTaylor(object = obj, H_B_prime = H_B_prime0[block[[i]], : Of the 25 strata, 1 strata have only one PSU. All
## strata with only one PSU are excluded from variance estimation. See the "singletonFix" argument for other options.

## Warning in getVarTaylor(object = obj, H_B_prime = H_B_prime0[block[[i]], : Of the 25 strata, 1 strata have only one PSU. All
## strata with only one PSU are excluded from variance estimation. See the "singletonFix" argument for other options.

## Warning in getVarTaylor(object = obj, H_B_prime = H_B_prime0[block[[i]], : Of the 25 strata, 1 strata have only one PSU. All
## strata with only one PSU are excluded from variance estimation. See the "singletonFix" argument for other options.
## Call:
## mml.sdf(formula = composite ~ B06011_001E_10K + dsex + pared,
##     data = linkAtt, weightVar = "origwt", idVar = "idvar")
## Summary Call:
## summary.mml.sdf(object = fit)
##
## Summary:
##                          Estimate   StdErr t.value
## (Intercept)             279.97052  3.02943 92.4170
## B06011_001E_10K           0.91175  0.91408  0.9975
## dsexFemale                0.73909  0.81260  0.9095
## paredGraduated HS        -0.25162  1.95133 -0.1289
## paredSome ed after HS     1.93552  1.58346  1.2223
## paredGraduated college    1.57703  1.82919  0.8621
## paredI don't know         0.79383  1.63351  0.4860
## paredOmitted              1.29527  1.46602  0.8835
## paredMultiple             0.53092  1.99222  0.2665
##
```

Drawing PVs

- Three of the generated items didn't get enough responses. So we removed them from the score card.

```r
'%!in%' <- function(x,y)!('%in%'(x,y))
fit$sCard <- fit$sCard[fit$sCard$key %!in%
                         c("m152602", "m2372cl", "m3498cl"),]
PVs <- drawPVs(linkAtt, fit, npv = 20L)
```

```
## Calculating posterior distribution for construct algebra (1 of 5)
## Calculating posterior distribution for construct data (2 of 5)
## Calculating posterior distribution for construct geometry (3 of 5)
## Calculating posterior distribution for construct measurement (4 of 5)
## Calculating posterior distribution for construct number (5 of 5)
## Calculating posterior correlation between construct algebra and data (1 of 10)
## Calculating posterior correlation between construct algebra and geometry (2 of 10)
## Calculating posterior correlation between construct algebra and measurement (3 of 10)
## Calculating posterior correlation between construct algebra and number (4 of 10)
## Calculating posterior correlation between construct data and geometry (5 of 10)
## Calculating posterior correlation between construct data and measurement (6 of 10)
## Calculating posterior correlation between construct data and number (7 of 10)
## Calculating posterior correlation between construct geometry and measurement (8 of 10)
## Calculating posterior correlation between construct geometry and number (9 of 10)
## Calculating posterior correlation between construct measurement and number (10 of 10)
## Generating plausible values.
```

Drawing PVs

Finally, here is the drawn plausible values. We can see the first plausible values of each subscale and the composite score.

```
PVs[1:5,c("algebra_dire1", "composite_dire1")]
```

```
##   algebra_dire1 composite_dire1
## 1      292.2637        287.8699
## 2      280.7014        293.9316
## 3      314.1876        296.7939
## 4      236.8094        233.3035
## 5      258.3922        249.1563
```

Self Reflection

1. Select a variables from ACS
2. Write your url
3. Download your ACS data
4. Clean up and scale your variable as needed
5. Merge with the simulated NAEP-like dataset
6. Build your own model (`composite ~ ACSvariable + simulatedDataVariable`)
7. Summarize the results
8. Draw new PVs

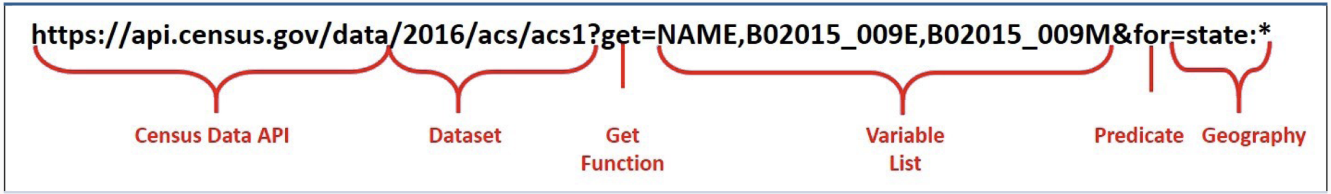
Self Reflection - Step 1: Select a variables

- Select a variable of your interest below:
  - B01001_001E (population)
  - B10063_002E : Household with grandparents living with grandchildren:
  - B19001_017E : Past 12 months income $200,000 or more
  - B27001_014E : Male 26 to 34 years with no health insurance coverage
  - B28010_007E : No Computer
  - B28011_008E : No Internet access
  - C16001_002E : Speak only English

For more variables: from https://api.census.gov/data/2019/acs/acs5/variables.html

Self Reflection - Step 2: Write your **url**

- Add your variable(s) to your *url* link



Source and more information

- Here is the set of links:

```
url1 = "https://api.census.gov/data/2019/acs/acs5?get=NAME,B01001_00
url2 = "https://api.census.gov/data/2019/acs/acs5?get=NAME,B01001_00
url3 = "https://api.census.gov/data/2019/acs/acs5?get=NAME,B01001_00
url4 = "https://api.census.gov/data/2019/acs/acs5?get=NAME,B01001_00
url5 = "https://api.census.gov/data/2019/acs/acs5?get=NAME,B01001_00
url6 = "https://api.census.gov/data/2019/acs/acs5?get=NAME,B01001_00
```

Self Reflection - Step 3. Download your ACS data

- Change your *url* name below (if you selected a different variable)

```
temp <- tempfile()
download.file(url6 , temp)
AcsDt6 <- read.table(temp, sep=",",header = TRUE)
```

```
## Warning in scan(file = file, what = what, sep = sep, quote = quote, dec = dec, : number of items read is not a multiple of the
## number of columns
```

```
unlink(temp)
head(AcsDt6)
```

```
##        X..NAME B01001_001E C16001_002E state zip.code.tabulation.area.  X
## 1 [ZCTA5 25245         600         600    54                    25245] NA
## 2 [ZCTA5 25268         964         834    54                    25268] NA
## 3 [ZCTA5 25286        1700        1667    54                    25286] NA
## 4 [ZCTA5 25303        6764        6109    54                    25303] NA
## 5 [ZCTA5 25311       10964       10090    54                    25311] NA
## 6 [ZCTA5 25419       11062        9830    54                    25419] NA
```

Self Reflection - Step 4. Clean your ACS data and scale

```
AcsDt6[,1] <- gsub(pattern="\\[", replacement="", x= AcsDt6[,1])
AcsDt6$X <- NULL
AcsDt6[,ncol(AcsDt6)] <- gsub(pattern="\\]",
                              replacement="",
                              x= AcsDt6[,ncol(AcsDt6)])
summary(AcsDt6)
```

```
##     X..NAME            B01001_001E        C16001_002E        state         zip.code.tabulation.area.
##  Length:33120       Min.   :     0.0   Min.   :    0   Min.   : 1.00   Length:33120
##  Class :character   1st Qu.:   705.8   1st Qu.:  610   1st Qu.:18.00   Class :character
##  Mode  :character   Median :  2801.0   Median : 2365   Median :30.00   Mode  :character
##                     Mean   :  9903.3   Mean   : 7221   Mean   :29.89
##                     3rd Qu.: 13475.2   3rd Qu.:10196   3rd Qu.:42.00
##                     Max.   :128294.0   Max.   :77013   Max.   :72.00
```

Self Reflection - Step 4. Clean your ACS data and scale

```
AcsDt6$EngSpeakers <- AcsDt6$C16001_002E/AcsDt6$B01001_001E
summary(AcsDt6$EngSpeakers)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  0.0000  0.8105  0.8945  0.8380  0.9325  1.0000     344
```

Self Reflection - Step 5. Merge with the simulated NAEP-like dataset

- Here we merge two datasets.

```
linkedData6 <- merge(simdf, AcsDt6, by.x = "zip",
                    by.y = "zip.code.tabulation.area.",
                    all.x = TRUE)
```

- Don't forget to rebind attributes of the `edsurvey.data.frame`.

```
linkAtt6 <- rebindAttributes(linkedData6, sNl)
```

Self Reflection - Step 6. Build your own model

- Here is an example: `composite ~ ACSvariable + simulatedDataVariable`

```
fitSR <- mml.sdf(composite ~ EngSpeakers + dsex + pared,
                 data = linkAtt6, weightVar='origwt', idVar="idvar")
```

```
## Warning in mml.sdf(composite ~ EngSpeakers + dsex + pared, data = linkAtt6, : m152602, m2372cl, m3498cl did not have enough
## parameters for the max score and will be taken out of analysis.
## Warning in mml.sdf(composite ~ EngSpeakers + dsex + pared, data = linkAtt6, : Removing 250 rows with NAs from analysis.
```

Self Reflection - Step 7. Summarize the results

```
summary(fitSR)
```

```
## Call:
## mml.sdf(formula = composite ~ EngSpeakers + dsex + pared, data = linkAtt6,
##     weightVar = "origwt", idVar = "idvar")
## Summary Call:
## summary.mml.sdf(object = fitSR)
##
## Summary:
##                          Estimate    StdErr t.value
## (Intercept)             282.49142   5.31272 53.1727
## EngSpeakers               0.27328   5.88009  0.0465
## dsexFemale                0.62971   0.80396  0.7833
## paredGraduated HS        -0.53478   2.00344 -0.2669
## paredSome ed after HS     1.72625   1.63548  1.0555
## paredGraduated college    1.61946   1.76090  0.9197
## paredI don't know         0.81701   1.63138  0.5008
## paredOmitted              1.39149   1.41960  0.9802
## paredMultiple             0.47635   1.93305  0.2464
##
## Residual Variance Estimate:
##               Estimate StdErr
## Population SD  39.1455     NA
```

Self Reflection - Step 8. Draw new PVs

```r
fitSR$sCard <- fitSR$sCard[fitSR$sCard$key %!in%
                              c("m152602", "m2372cl", "m3498cl"),]
pvSR <- drawPVs(linkAtt6, fitSR, npv= 20L)
```

```
## Calculating posterior distribution for construct algebra (1 of 5)
## Calculating posterior distribution for construct data (2 of 5)
## Calculating posterior distribution for construct geometry (3 of 5)
## Calculating posterior distribution for construct measurement (4 of 5)
## Calculating posterior distribution for construct number (5 of 5)
## Calculating posterior correlation between construct algebra and data (1 of 10)
## Calculating posterior correlation between construct algebra and geometry (2 of 10)
## Calculating posterior correlation between construct algebra and measurement (3 of 10)
## Calculating posterior correlation between construct algebra and number (4 of 10)
## Calculating posterior correlation between construct data and geometry (5 of 10)
## Calculating posterior correlation between construct data and measurement (6 of 10)
## Calculating posterior correlation between construct data and number (7 of 10)
## Calculating posterior correlation between construct geometry and measurement (8 of 10)
## Calculating posterior correlation between construct geometry and number (9 of 10)
## Calculating posterior correlation between construct measurement and number (10 of 10)
## Generating plausible values.
```

Wrap Up

NATIONAL ASSESSMENT OF EDUCATIONAL PROGRESS

Learning EdSurvey

- Reading vignettes provided in training materials

```
vignette("introduction", package="EdSurvey")
```

- R help

```
help(package = "EdSurvey")
```

- EdSurvey eBook
- EdSurvey Website
- EdSurvey Github
- NAEP Data Training workshop

Under development

- Package is still under development
  - Subsequent releases of the EdSurvey package will provide additional functionality for NAEP linking errors and direct estimation.
- Your feedback is important to us!

Contact Information

EdSurvey Package Help

- EdSurvey.help@air.org

EdSurvey Package Help on NCES.ed.gov

- http://nces.ed.gov/nationsreportcard/contactus.aspx

Ting Zhang

- tzhang@air.org

Paul Bailey

- pbailey@air.org

Emmanuel Sikali

- Emmanuel.Sikali@ed.gov