

# ACE Models with the NLSY

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## Abstract

We describe how to use the NlsyLinks package to examine various biometric models, using the NLSY79.

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## 1 Terminology

Researchers and grad students interested using the NLSY for Behavior Genetics and family research, please start with our 2016 article, *The NLSY Kinship Links: Using the NLSY79 and NLSY-Children Data to Conduct Genetically-Informed and Family-Oriented Research*.

This package considers both Gen1 and Gen2 subjects. **Gen1** refers to subjects in the original NLSY79 sample (<http://www.bls.gov/nls/nlsy79.htm>). **Gen2** subjects are the biological offspring of the Gen1 females -i.e., those in the NLSY79 Children and Young Adults sample (<http://www.bls.gov/nls/nlsy79ch.htm>). The NLSY97 is a third dataset that can be used for behavior genetic research (<http://www.bls.gov/nls/nlsy97.htm>), although this vignette focuses on the two generations in the NLSY79.

Standard terminology is to refer Gen2 subjects as ‘children’ when they are younger than age 15 (NLSY79-C), and as ‘young adults’ when they are 15 and older (NLSY79-YA); though they are the same respondents, different funding mechanisms and different survey items necessitate the distinction. This cohort is sometimes abbreviated as ‘NLSY79-C’, ‘NLSY79C’, ‘NLSY-C’ or ‘NLSYC’.

Within our own team, we’ve mostly stopped using terms like ‘NLSY79’, ‘NLSY79-C’ and ‘NLSY79-YA’, because we conceptualize it as one big sample containing two related generations. In many senses, the responses collected from the second generation can be viewed as outcomes of the first generation. Likewise, the parents in the first generation provide many responses that can be viewed as explanatory variables for the 2nd generation. Depending on your research, there can be big advantages of using one cohort to augment the other. There are also survey items that provide information about the 3rd generation and the 0th generation.

The **SubjectTag** variable uniquely identifies NLSY79 subjects when a dataset contains both generations. For Gen2 subjects, the **SubjectTag** is identical to their CID (i.e., C00001.00 -the ID assigned in the NLSY79-Children files). However for Gen1 subjects, the **SubjectTag** is their CaseID (i.e., R00001.00), with “00” appended. This manipulation is necessary to identify subjects uniquely in inter-generational datasets. A Gen1 subject with an ID of 43 becomes 4300. The **SubjectTags** of her four children remain 4301, 4302, 4303, and 4304.

The **expected coefficient of relatedness** of a pair of subjects is typically represented by the statistical variable  $R$ . Examples are: Monozygotic twins have  $R=1$ ; dizygotic twins have  $R=0.5$ ; full siblings (i.e., those who share both biological parents) have  $R=0.5$ ; half-siblings (i.e., those who share exactly one biological parent) have  $R=0.25$ ; adopted siblings have  $R=0.0$ . Other uncommon possibilities are mentioned in the documentation for **Links79Pair**. The font (and hopefully their context) should distinguish the variable  $R$  from the software R. To make things slightly more confusing the computer variable for  $R$  in the **Links79Pair** dataset is written with a monospace font: `R`.

A subject’s **ExtendedID** indicates their extended family. Two subjects will be in the same extended family if either: [1] they are Gen1 housemates, [2] they are Gen2 siblings, [3] they are Gen2 cousins (i.e., they have mothers who are Gen1 sisters in the NLSY79), [4] they are mother and child (in Gen1 and Gen2, respectively), or [5] they are (aunt—uncle) and (niece—nephew) (in Gen1 and Gen2, respectively).

An **outcome variable** is directly relevant to the applied researcher; these might represent constructs like height, IQ, and income. A **plumbing variable** is necessary to manage BG datasets; examples are `R`, a subject’s ID, and the date of a subject’s last survey.

An ACE model is the basic biometrical model used by Behavior Genetic researchers, where the genetic and environmental effects are assumed to be additive. The three primary variance components are (1) the proportion of variability due to a shared genetic influence (typically represented as  $a^2$ , or sometimes  $h^2$ ), (2) the proportion of variability due to shared common environmental influence (typically  $c^2$ ), and (3) the proportion of variability due to unexplained/residual/error influence (typically  $e^2$ ).

The variables are scaled so that they account for all observed variability in the outcome variable; specifically:  $a^2 + c^2 + e^2 = 1$ . Using appropriate designs that can logically distinguish these different components (under carefully specified assumptions), the basic biometrical modeling strategy is to estimate the magnitude of  $a^2$ ,  $c^2$ , and  $e^2$  within the context of a particular model. For gentle introductions to Behavior Genetic research, we recommend Plomin (1990) and Carey (2003). For more in-depth ACE model-fitting strategies, we recommend Neale & Maes, (1992).

The **NLS Investigator** (<http://www.nlsinfo.org/investigator/>) is the best way to obtain the NLSY79 and NLSY97 datasets. See our vignette dedicated to the NLS Investigator by typing

`vignette("NlsInvestigator")` or by visiting <https://cran.r-project.org/package=NlsyLinks>.

Before starting the real examples, first verify that the `NlsyLinks` package is installed correctly. If not, please refer to [Appendix C](#).

```
any(.packages(all.available=TRUE) == "NlsyLinks") #Should evaluate to TRUE.
## [1] TRUE

library(NlsyLinks) #Load the package into the current session.

##
## Attaching package: 'NlsyLinks'
## The following object is masked _by_ '.GlobalEnv':
##
## ExtraOutcomes79
```

The package's documentation manual can be opened by typing `?NlsyLinks` in R or clicking the appropriate entry in RStudio's 'Packages' tab (which is usually in the lower right panel).

## 2 Example: DF analysis with a Simple Outcome for Gen2 Subjects, Using a Package Variable

The vignette's first example uses a simple statistical model and all available Gen2 subjects. The `CreatePairLinksDoubleEntered` function will create a data frame where each represents one pair of siblings, respective of order (*i.e.*, there is a row for Subjects 201 and 202, and a second row for Subjects 202 and 201). This function examines the subjects' IDs and determines who is related to whom (and by how much). By default, each row it produces has at least six values/columns: (i) ID for the older member of the kinship pair: `Subject1Tag`, (ii) ID for the younger member: `Subject2Tag`, (iii) ID for their extended family: `ExtendedID`, (iv) their estimated coefficient of genetic relatedness: `R`, (v *and beyond*) outcome values for the older member; (vi *and beyond*) outcome values for the younger member.

A DeFries-Fulker (DF) Analysis uses linear regression to estimate the  $a^2$ ,  $c^2$ , and  $e^2$  of a univariate biometric system. The interpretations of the DF analysis can be found in Rodgers & Kohler (2005) and Rodgers, Rowe, & Li (1999). This vignette example uses the newest variation, which estimates two parameters; the corresponding function is called `DeFriesFulkerMethod3`. The steps are:

1. Use the [NLS Investigator](#) to select and download a Gen2 dataset.
2. Open R and create a new script (see [Appendix B](#)) and load the `NlsyLinks` package. If you haven't done so, first install the `NlsyLinks` package (see [Appendix C](#)).
3. Within the R script, load the linking dataset. Then select only Gen2 subjects. The 'Pair' version of the linking dataset is essentially an upper triangle of a symmetric sparse matrix.
4. Load and assign the `ExtraOutcomes79` dataset.
5. Specify the outcome variable name and filter out all subjects who have a negative value in this variable. The NLSY typically uses negative values to indicate different types of missingness (see 'Further Information' below).
6. Create a double-entered file by calling the `CreatePairLinksDoubleEntered` function. At minimum, pass the (i) outcome dataset, the (ii) linking dataset, and the (iii) name(s) of the outcome variable(s). (*There are occasions when a single-entered file is more appropriate for a DF analysis. See Rodgers & Kohler, 2005, for additional information.*)
7. Use `DeFriesFulkerMethod3` function (*i.e.*, general linear model) to estimate the coefficients of the DF model.

```
### R Code for Example DF analysis with a simple outcome and Gen2 subjects
```

```
#Step 2: Load the package containing the linking routines.
```

```
library(NlsyLinks)
```

```
#Step 3: Load the LINKING dataset and filter for the Gen2 subjects
```

```
dsLinking <- subset(Links79Pair, RelationshipPath=="Gen2Siblings")
```

```
summary(dsLinking) #Notice there are 11,088 records (one for each unique pair).
```

```
##      ExtendedID      SubjectTag_S1      SubjectTag_S2      R
##  Min.      :    2      Min.      :   201      Min.      :   202      Min.      :0.250
## 1st Qu.: 3155      1st Qu.: 315501      1st Qu.: 315503      1st Qu.:0.250
##  Median : 6114      Median : 611403      Median : 611404      Median :0.500
##  Mean   : 5933      Mean   : 593658      Mean   : 593660      Mean   :0.417
## 3rd Qu.: 8511      3rd Qu.: 851101      3rd Qu.: 851103      3rd Qu.:0.500
##  Max.   :12673      Max.   :1267301      Max.   :1267302      Max.   :1.000
##      RelationshipPath
## Gen1Housemates:    0
## Gen2Siblings   :11088
## Gen2Cousins    :    0
## ParentChild    :    0
## AuntNiece      :    0
##
```

```
#Step 4: Load the OUTCOMES dataset, and then examine the summary.
```

```
dsOutcomes <- ExtraOutcomes79 #'ds' stands for 'Data Set'
```

```
summary(dsOutcomes)
```

```
##      SubjectTag      SubjectID      Generation      HeightZGenderAge      WeightZGenderAge
##  Min.      :   100      Min.      :    1      Min.      :1.000      Min.      :-2.985      Min.      :-2.985
## 1st Qu.: 314025      1st Qu.:   5998      1st Qu.:1.000      1st Qu.: -0.724      1st Qu.: -0.677
##  Median : 620050      Median :  12000      Median :1.000      Median : -0.045      Median : -0.149
##  Mean   : 618600      Mean   : 289254      Mean   :1.476      Mean   : -0.006      Mean   :  0.001
## 3rd Qu.: 914501      3rd Qu.: 577403      3rd Qu.:2.000      3rd Qu.:  0.648      3rd Qu.:  0.533
##  Max.   :1268600      Max.   :1267501      Max.   :2.000      Max.   :  2.996      Max.   :  4.945
##                                     NA's      :4711      NA's      :4719
## AfqtRescaled2006Gaussified      Afi      Afm      MathStandardized
##  Min.      :-2.895      Min.      : 2.00      Min.      : 0.00      Min.      : 65.0
## 1st Qu.: -0.692      1st Qu.:15.00      1st Qu.:12.00      1st Qu.:  92.5
##  Median : -0.024      Median :17.00      Median :13.00      Median :100.0
##  Mean   : -0.011      Mean   :16.66      Mean   :12.78      Mean   :100.1
## 3rd Qu.:  0.660      3rd Qu.:18.00      3rd Qu.:14.00      3rd Qu.:108.5
##  Max.   :  2.994      Max.   :27.00      Max.   :19.00      Max.   :135.0
##  NA's      :12510      NA's      :12740      NA's      :18165      NA's      :15085
```

```
#Step 5: This step isn't necessary for this example, because Kelly Meredith already
```

```
# groomed the values. If the negative values (which represent NLSY missing or
```

```
# skip patterns) still exist, then:
```

```
dsOutcomes$MathStandardized[dsOutcomes$MathStandardized < 0] <- NA
```

```
#Step 6: Create the double entered dataset.
```

```
dsDouble <- CreatePairLinksDoubleEntered(
```

```
  outcomeDataset = dsOutcomes,
```

```
  linksPairDataset = dsLinking,
```

```
  outcomeNames = c('MathStandardized')
```

```
)
```

```
summary(dsDouble) #Notice there are 22176=(2*11088) records now (two for each unique pair).

## SubjectTag_S1      SubjectTag_S2      ExtendedID      R
## Min.      :    201  Min.      :    201  Min.      :    2  Min.      :0.250
## 1st Qu.: 315502  1st Qu.: 315502  1st Qu.: 3155  1st Qu.:0.250
## Median : 611404  Median : 611404  Median : 6114  Median :0.500
## Mean   : 593659  Mean   : 593659  Mean   : 5933  Mean   :0.417
## 3rd Qu.: 851102  3rd Qu.: 851102  3rd Qu.: 8511  3rd Qu.:0.500
## Max.   :1267302  Max.   :1267302  Max.   :12673  Max.   :1.000
##
## RelationshipPath MathStandardized_S1 MathStandardized_S2
## Gen1Housemates:  0  Min.      : 65.00  Min.      : 65.00
## Gen2Siblings   :22176 1st Qu.: 90.00  1st Qu.: 90.00
## Gen2Cousins    :  0  Median : 98.50  Median : 98.50
## ParentChild   :  0  Mean   : 98.39  Mean   : 98.39
## AuntNiece     :  0  3rd Qu.:107.00  3rd Qu.:107.00
##               Max.   :135.00  Max.   :135.00
##               NA's   :3885    NA's   :3885

#Step 7: Estimate the ACE components with a DF Analysis
ace <- DeFriesFulkerMethod3(
  dataSet = dsDouble,
  oName_S1 = "MathStandardized_S1",
  oName_S2 = "MathStandardized_S2")
ace

## [1] "Results of ACE estimation: [show]"
## ASquared CSquared ESquared CaseCount
## 7.734732e-01 1.468498e-01 7.967703e-02 1.668000e+04
```

*Further Information:* If the different reasons of missingness are important, further work is necessary. For instance, some analyses that use item Y19940000 might need to distinguish a response of “Don’t Know” (which is coded as -2) from “Missing” (which is coded as -7). For this vignette example, we’ll assume it’s safe to clump the responses together.

### 3 Example: DF analysis with a univariate outcome from a Gen2 Extract

The vignette’s second example differs from the previous example in two ways. First, the outcome variables are read from a CSV ([comma separated values](#) file) that was downloaded from the [NLS Investigator](#). Second, the DF analysis is called through the function `AceUnivariate`; this function is a wrapper around some simple ACE methods, and will help us smoothly transition to more techniques later in the vignette.

The steps are:

1. Use the [NLS Investigator](#) to select and download a Gen2 dataset. Select the variables ‘length of gestation of child in weeks’ (C03280.00), ‘weight of child at birth in ounces’ (C03286.00), and ‘length of child at birth’ (C03288.00), and then download the \*.zip file to your local computer.
2. Open R and create a new script (see [Appendix B](#)) and load the `NlsyLinks` package.
3. Within the R script, load the linking dataset. Then select only Gen2 subjects.
4. Read the CSV into R as a `data.frame` using `ReadCsvNlsy79Gen2`.
5. Verify the desired outcome column exists, and rename it something meaningful to your project. It is important that the `data.frame` is reassigned (*i.e.*, `ds <- RenameNlsyColumn(...)`). In this example, we

rename column C0328800 to BirthWeightInOunces.

6. Filter out all subjects who have a negative BirthWeightInOunces value. See the 'Further Information' note in the previous example.
7. Create a double-entered file by calling the CreatePairLinksDoubleEntered function. At minimum, pass the (i) outcome dataset, the (ii) linking dataset, and the (iii) name(s) of the outcome variable(s).
8. Call the AceUnivariate function to estimate the coefficients.

```
### R Code for Example of a DF analysis with a simple outcome and Gen2 subjects
#Step 2: Load the package containing the linking routines.
library(NlsyLinks)

#Step 3: Load the linking dataset and filter for the Gen2 subjects
dsLinking <- subset(Links79Pair, RelationshipPath=="Gen2Siblings")

#Step 4: Load the outcomes dataset from the hard drive and then examine the summary.
# Your path might be: filePathOutcomes <- 'C:/BGRsearch/NlsExtracts/gen2-birth.csv'
filePathOutcomes <- file.path(path.package("NlsyLinks"), "extdata", "gen2-birth.csv")
dsOutcomes <- ReadCsvNlsy79Gen2(filePathOutcomes)
summary(dsOutcomes)
```

##	SubjectTag	SubjectID	ExtendedID	Generation	SubjectTagOfMother
##	Min. : 201	Min. : 201	Min. : 2	Min. :2	Min. : 200
##	1st Qu.: 310302	1st Qu.: 310302	1st Qu.: 3101	1st Qu.:2	1st Qu.: 310300
##	Median : 604607	Median : 604607	Median : 6045	Median :2	Median : 604600
##	Mean : 601313	Mean : 601313	Mean : 6007	Mean :2	Mean : 601311
##	3rd Qu.: 876203	3rd Qu.: 876203	3rd Qu.: 8757	3rd Qu.:2	3rd Qu.: 876200
##	Max. :1267501	Max. :1267501	Max. :12675	Max. :2	Max. :1267500
##			NA's :2		
##	C0005300	C0005400	C0005700	C0328000	C0328600
##	Min. :1.000	Min. :-3.000	Min. : -3	Min. :-7.00	Min. : -7.0
##	1st Qu.:2.000	1st Qu.: 1.000	1st Qu.:1981	1st Qu.:37.00	1st Qu.: 99.0
##	Median :3.000	Median : 1.000	Median :1985	Median :39.00	Median :115.0
##	Mean :2.338	Mean : 1.489	Mean :1986	Mean :33.51	Mean :103.9
##	3rd Qu.:3.000	3rd Qu.: 2.000	3rd Qu.:1990	3rd Qu.:39.00	3rd Qu.:128.0
##	Max. :3.000	Max. : 2.000	Max. :2008	Max. :51.00	Max. :768.0
##					
##	C0328800				
##	Min. :-7.00				
##	1st Qu.:18.00				
##	Median :20.00				
##	Mean :16.51				
##	3rd Qu.:21.00				
##	Max. :48.00				
##					

```
#Step 5: Verify and rename an existing column.
VerifyColumnExists(dsOutcomes, "C0328600") #Should return '10' in this example.

## [1] 10

dsOutcomes <- RenameNlsyColumn(dsOutcomes, "C0328600", "BirthWeightInOunces")

#Step 6: For this item, a negative value indicates the parent refused, didn't know,
# invalidly skipped, or was missing for some other reason.
# For our present purposes, we'll treat these responses equivalently.
```

```

# Then clip/winsorized/truncate the weight to something reasonable.
dsOutcomes$BirthWeightInOunces[dsOutcomes$BirthWeightInOunces < 0] <- NA
dsOutcomes$BirthWeightInOunces <- pmin(dsOutcomes$BirthWeightInOunces, 200)

#Step 7: Create the double entered dataset.
dsDouble <- CreatePairLinksDoubleEntered(
  outcomeDataset = dsOutcomes,
  linksPairDataset = dsLinking,
  outcomeNames = c('BirthWeightInOunces')
)

#Step 8: Estimate the ACE components with a DF Analysis
ace <- AceUnivariate(
  method = "DeFriesFulkerMethod3",
  dataSet = dsDouble,
  oName_S1 = "BirthWeightInOunces_S1",
  oName_S2 = "BirthWeightInOunces_S2"
)
ace

## [1] "Results of ACE estimation: [show]"
##      ASquared      CSquared      ESquared      CaseCount
## 5.041607e-01 1.776613e-01 3.181780e-01 1.744000e+04

```

For another example of incorporating CSVs downloaded from the NLS Investigator, please see the “Race and Gender Variables” entry in the [FAQ](#).

## 4 Example: Multiple Group SEM of a Simple Outcome for Gen2 Subjects

The example differs from the first one by the statistical mechanism used to estimate the components. The first example uses multiple regression to estimate the influence of the shared genetic and environmental factors, while this example uses structural equation modeling (SEM).

The `CreatePairLinksSingleEntered` function will create a `data.frame` where each row represents one unique pair of siblings, *irrespective of order*. Other than producing half the number of rows, this function is identical to `CreatePairLinksDoubleEntered`.

The steps are:

(Steps 1-5 proceed identically to the first example.)

6. Create a *single*-entered file by calling the `CreatePairLinksSingleEntered` function. At minimum, pass the (i) outcome dataset, the (ii) linking dataset, and the (iii) name(s) of the outcome variable(s).
7. Declare the names of the outcome variables corresponding to the two members in each pair. Assuming the variable is called ‘ZZZ’ and the preceding steps have been followed, the variable ‘ZZZ\_S1’ corresponds to the first members and ‘ZZZ\_S2’ corresponds to the second members.
8. Create a `GroupSummary data.frame`, which identifies the R groups that should be considered by the model. Inspect the output to see if the groups show unexpected or fishy differences.
9. Create a `data.frame` with cleaned variables to pass to the SEM function. This `data.frame` contains only the three necessary rows and columns.
10. Estimate the SEM with the `lavaan` package. The function returns an S4 object, which shows the basic ACE information.



11. Inspect details of the SEM, beyond the ACE components. In this example, we look at the fit stats and the parameter estimates. The *lavaan* package has additional methods that may be useful for your purposes.

```
### R Code for Example lavaan estimation analysis with a simple outcome and Gen2 subjects
#Steps 1-5 are explained in the vignette's first example:
library(NlsyLinks)
dsLinking <- subset(Links79Pair, RelationshipPath=="Gen2Siblings")
dsOutcomes <- ExtraOutcomes79
dsOutcomes$MathStandardized[dsOutcomes$MathStandardized < 0] <- NA

#Step 6: Create the single entered dataset.
dsSingle <- CreatePairLinksSingleEntered(
  outcomeDataset = dsOutcomes,
  linksPairDataset = dsLinking,
  outcomeNames = c('MathStandardized')
)

#Step 7: Declare the names for the two outcome variables.
oName_S1 <- "MathStandardized_S1" #Stands for Outcome1
oName_S2 <- "MathStandardized_S2" #Stands for Outcome2

#Step 8: Summarize the R groups and determine which groups can be estimated.
dsGroupSummary <- RGroupSummary(dsSingle, oName_S1, oName_S2)
dsGroupSummary
```

##	R	Included	PairCount	O1Mean	O2Mean	O1Variance	O2Variance	O1O2Covariance
## 1	0.250	TRUE	2691	95.11427	95.98105	126.8906	150.1054	42.04343
## 2	0.375	TRUE	133	93.54135	93.41353	163.0721	131.5588	46.56042
## 3	0.500	TRUE	5493	99.88831	100.02339	168.7349	172.9167	90.12465
## 4	0.750	FALSE	2	108.50000	106.00000	220.5000	18.0000	63.00000
## 5	1.000	TRUE	21	98.21429	96.02381	289.4393	215.2369	229.10714

```
## Correlation Determinant PosDefinite
## 1 0.3046389 17279.309 TRUE
## 2 0.3178829 19285.695 TRUE
## 3 0.5276218 21054.625 TRUE
## 4 1.0000000 0.000 FALSE
## 5 0.9179130 9807.933 TRUE

#Step 9: Create a cleaned dataset
dsClean <- CleanSemAceDataset(dsDirty=dsSingle, dsGroupSummary, oName_S1, oName_S2)

#Step 10: Run the model
ace <- AceLavaanGroup(dsClean)
ace
```

```
## [1] "Results of ACE estimation: [show]"
## ASquared CSquared ESquared CaseCount
## 0.6210977 0.2100356 0.1688667 8338.0000000

#Notice the `CaseCount' is 8,390 instead of 17,440.
# This is because (a) one pair with R=.75 was excluded, and
# (b) the SEM uses a single-entered dataset instead of double-entered.
#

#Step 11: Inspect the output further
library(lavaan) #Load the package to access methods of the lavaan class.
```



```

GetDetails(ace)

## lavaan 0.6-3 ended normally after 54 iterations
##
##      Optimization method          NLMINB
##      Number of free parameters      32
##      Number of equality constraints   28
##
##      Number of observations per group
##      1                             2691
##      2                             133
##      3                             5493
##      4                             21
##
##      Estimator                      ML
##      Model Fit Test Statistic       447.303
##      Degrees of freedom             16
##      P-value (Chi-square)           0.000
##
## Chi-square for each group:
##
##      1                             281.432
##      2                             31.252
##      3                             127.180
##      4                             7.439

#Examine fit stats like Chi-Squared, RMSEA, CFI, etc.
fitMeasures(GetDetails(ace)) #'fitMeasures' is defined in the lavaan package.

##      npar      fmin      chisq      df
##      4.000      0.027      447.303      16.000
##      pvalue      baseline.chisq      baseline.df      baseline.pvalue
##      0.000      2107.252      4.000      0.000
##      cfi      tli      nnfi      rfi
##      0.795      0.949      0.949      NA
##      nfi      pnfi      ifi      rni
##      NA      3.151      0.794      0.795
##      logl      unrestricted.logl      aic      bic
##      -65103.976      -64880.324      130215.952      130244.066
##      ntotal      bic2      rmsea      rmsea.ci.lower
##      8338.000      130231.355      0.114      0.105
##      rmsea.ci.upper      rmsea.pvalue      rmr      rmr_nomean
##      0.123      0.000      10.095      12.901
##      srmr      srmr_bentler      srmr_bentler_nomean      crmr
##      0.130      0.130      0.090      0.182
##      crmr_nomean      srmr_mplus      srmr_mplus_nomean      cn_05
##      0.026      0.156      0.084      491.178
##      cn_01      gfi      agfi      pgfi
##      597.499      0.999      0.999      0.799
##      mfi
##      0.974

#Examine low-level details like each group's individual parameter estimates and standard
# errors. Uncomment the next line to view the entire output (which is roughly 4 pages).
#summary(GetDetails(ace))

```

## 5 Example: Multiple Group SEM of a Simple Outcome for Gen1 Subjects

The example differs from the previous one in three ways. First, Gen1 subjects are used. Second, standardized height is used instead of math. Third, pairs are dropped if their  $R$  is zero; we return to this last issue after the code is run.

```
### R Code for Example lavaan estimation analysis with a simple outcome and Gen1 subjects
#Steps 1-5 are explained in the vignette's first example:
library(NlsyLinks)
dsLinking <- subset(Links79Pair, RelationshipPath=="Gen1Housemates")
dsOutcomes <- ExtraOutcomes79
#The HeightZGenderAge variable is already groomed

#Step 6: Create the single entered dataset.
dsSingle <- CreatePairLinksSingleEntered(
  outcomeDataset = dsOutcomes,
  linksPairDataset = dsLinking,
  outcomeNames = c('HeightZGenderAge'))

#Step 7: Declare the names for the two outcome variables.
oName_S1 <- "HeightZGenderAge_S1"
oName_S2 <- "HeightZGenderAge_S2"

#Step 8: Summarize the R groups and determine which groups can be estimated.
dsGroupSummary <- RGroupSummary(dsSingle, oName_S1, oName_S2)
dsGroupSummary

##      R Included PairCount      O1Mean      O2Mean O1Variance O2Variance O1O2Covariance
## 1 0.25      TRUE      280  0.04830041  0.056049671  1.0181579  1.1847214      0.2655632
## 2 0.50      TRUE     3894 -0.04986899 -0.027888465  0.9735617  1.0193789      0.4660286
## 3 1.00      TRUE       11 -0.08652006 -0.009039755  0.3171247  0.9518269      0.3583306
##      Correlation Determinant PosDefinite
## 1  0.2417977  1.1357096      TRUE
## 2  0.4678030  0.7752456      TRUE
## 3  0.6522137  0.1734469      TRUE

#Step 9: Create a cleaned dataset
dsClean <- CleanSemAceDataset(dsDirty=dsSingle, dsGroupSummary, oName_S1, oName_S2)

#Step 10: Run the model
ace <- AceLavaanGroup(dsClean)
ace

## [1] "Results of ACE estimation: [show]"
##      ASquared      CSquared      ESquared      CaseCount
##      0.7040149      0.1123658      0.1836193  4185.0000000

#Step 11: Inspect the output further (see the final step in the previous example).
```

Most of them responded they were **Non-relatives** to the explicit items asked in 1979 (*i.e.*, NLSY79 variables R00001.50 through R00001.59). Yet their height's observed correlations is far larger than would be expected for a sample of unrelated subjects. Since our team began BG research with the NLSY in the mid-1990s, the  $R=0$  group has consistently presented higher than expected correlations, across many domains of outcome variables. For a long time, we have substantial doubts that subject pairs in this group share a low proportion of their selective genes. Consequently, we suggest applied researchers consider excluding this group from

their biometric analyses.

If you wish to exclude additional groups from the analyses, Step 8 should change slightly. For instance, to MZ twins, replace the two lines in Step 8 with the following four. This is most for demonstration. It is unlikely to be useful idea in the current example, and is more likely to be useful when using the `RFull` variable, which includes all values of *R* we were able to determine.

```
#Step 8: Summarize the R groups and determine which groups can be estimated.
dsGroupSummary <- RGroupSummary(dsSingle, oName_S1, oName_S2)
rGroupsToDrop <- c( 1 )
dsGroupSummary[dsGroupSummary$R %in% rGroupsToDrop, "Included"] <- FALSE
dsGroupSummary
```

## 6 Example: Multiple Group SEM of a Simple Outcome all pairs in Gen1 and Gen2

The example differs from the previous example in one way –all possible pairs are considered for the analysis. Pairs are only excluded (a) if they belong to one of the small *R* groups that are difficult to estimate, or (b) if the value for adult height is missing. This includes all 42,773 relationships in the follow five types of NLSY79 relationships.

	Relationship Frequency
Gen1Housemates	5,302
Gen2Siblings	11,088
Gen2Cousins	4,995
ParentChild	11,504
AuntNiece	9,884

Table 1: Number of NLSY79 relationship, by `RelationshipPath`. (Recall that ‘AuntNiece’ also contains uncles and nephews.)

In our opinion, using the intergenerational links is one of the most exciting new opportunities for NLSY researchers to pursue. We will be happy to facilitate such research through consult or collaboration, or even by generating new data structures that may be of value. The complete kinship linking file facilitates many different kinds of cross-generational research, using both biometrical and other kinds of modeling methods.

```
### R Code for Example lavaan estimation analysis with a simple outcome and Gen1 subjects
#Steps 1-5 are explained in the vignette's first example:
library(NlsyLinks)
dsLinking <- subset(Links79Pair, RelationshipPath %in%
                    c("Gen1Housemates", "Gen2Siblings", "Gen2Cousins",
                      "ParentChild", "AuntNiece"))
#Because all five paths are specified, the line above is equivalent to:
#dsLinking <- Links79Pair

dsOutcomes <- ExtraOutcomes79
#The HeightZGenderAge variable is already groomed

#Step 6: Create the single entered dataset.
dsSingle <- CreatePairLinksSingleEntered(
  outcomeDataset = dsOutcomes,
  linksPairDataset = dsLinking,
  outcomeNames = c('HeightZGenderAge'))
```

```

#Step 7: Declare the names for the two outcome variables.
oName_S1 <- "HeightZGenderAge_S1"
oName_S2 <- "HeightZGenderAge_S2"

#Step 8: Summarize the R groups and determine which groups can be estimated.
dsGroupSummary <- RGroupSummary(dsSingle, oName_S1, oName_S2)
dsGroupSummary

##           R Included PairCount      O1Mean      O2Mean O1Variance O2Variance
## 1 0.0625      TRUE      202  0.22968753 -0.07575395  1.0509023  0.8271487
## 2 0.1250      TRUE     2422 -0.02213186  0.01502572  1.0334694  0.9809845
## 3 0.2500      TRUE     7135 -0.05440190 -0.03888026  1.0190843  1.0295914
## 4 0.3750      TRUE      46  0.22002194 -0.10598270  1.0661876  0.9615586
## 5 0.5000      TRUE    14865 -0.05762688 -0.01739297  0.9603521  0.9849298
## 6 0.7500     FALSE      0           NA           NA           NA           NA
## 7 1.0000      TRUE      27 -0.11092113 -0.12601206  0.6934418  0.9891146
##      O1O2Covariance Correlation Determinant PosDefinite
## 1      0.1112158      0.1192871      0.8568836          TRUE
## 2      0.1487539      0.1477368      0.9916897          TRUE
## 3      0.2721448      0.2656823      0.9751776          TRUE
## 4      0.4293439      0.4240339      0.8408656          TRUE
## 5      0.4146052      0.4263016      0.7739818          TRUE
## 6           NA           NA           NA          FALSE
## 7      0.6863894      0.8287857      0.2147630          TRUE

#Step 9: Create a cleaned dataset
dsClean <- CleanSemAceDataset(dsDirty=dsSingle, dsGroupSummary, oName_S1, oName_S2)

#Step 10: Run the model
ace <- AceLavaanGroup(dsClean)
ace

## [1] "Results of ACE estimation: [show]"
##      ASquared      CSquared      ESquared      CaseCount
## 7.364675e-01 6.586520e-02 1.976673e-01 2.469700e+04

#Step 11: Inspect the output further (see the final step two examples above).

```

Notice the ACE estimates are very similar to the previous version, but the number of pairs has increased by 6x—from 4,185 to 24,700. The number of *subjects* doubles when Gen2 is added, and the number of *relationship pairs* really takes off. When an extended family's entire pedigree is considered by the model, many more types of links are possible than if just nuclear families are considered. This increased statistical power is even more important when the population's  $a^2$  is small or moderate, instead of something large like 0.7.

You may notice that the analysis has 24,697 relationships instead of the entire 42,773. This is primarily because not all subjects have a value for 'adult height' (and that's mostly because a lot of Gen2 subjects are too young). There are 42,025 pairs with a nonmissing value in `RFull`, meaning that 98.3% are classified. We feel comfortable claiming that if a researcher has a phenotype for both members of a pair, there's a 99+% chance we have an `RFull` for it. For a description of the `R` and `RFull` variables, please see the `Links79Pair` entry in the package [reference manual](#).

## References:

The standard errors (but not the coefficients) are biased downward in these analyses, because individuals are included in multiple pairs. Our MDAN article presents a [GEE](#) method for handling this (p. 572). The CARB model (or any model that treats the full pedigree as a single unit of analysis in the multivariate or

multilevel sense) also would produce more accurate standard error estimates.

One of our [2013 BGA presentations](#) discusses these benefits in the context of the current NlsyLinks package, and our 2008 MDAN article accomplishes something similar using a GEE with females in both generations.

Bard, D.E., Beasley, W.H., Meredith, K., & Rodgers, J.L. (2012). *Biometric Analysis of Complex NLSY Pedigrees: Introducing a Conditional Autoregressive Biometric (CARB) Mixed Model*. Behavior Genetics Association 42nd Annual Meeting. [\[Slides\]](#)

Beasley, W.H., Bard, D.E., Meredith, K., Hunter, M., & Rodgers, J.L. (2013). *NLSY Kinship Links: Creating Biometrical Design Structures from Cross-Generational Data*. Behavior Genetics Association 43rd Annual Meeting. [\[Slides\]](#)

Rodgers, J. L., Bard, D., Johnson, A., D’Onofrio, B., & Miller, W. B. (2008). [The Cross-Generational Mother-Daughter-Aunt-Niece Design: Establishing Validity of the MDAN Design with NLSY Fertility Variables](#). *Behavior Genetics*, 38, 567-578.

## 7 Example: Midstream data manipulation with SAS

*Mike Hunter is writing a separate vignette for this example. The SAS code is complete, and the surrounding text is the only thing remaining. Contact us if you’re interested in a pre-release version. We’ll post the polished version in the ‘[other-software](#)’ location in our online [forums](#) within the next 2-4 weeks.*

The example differs from the previous example in one substantial way: After R is used to link the related pairs, and connect them to their outcome values, the dataset is exported so that the user can further manipulate the data in SAS.

After a presentation, several audience members at the 2012 BGA meeting informed us that this vignette example would help them be more efficient. This approach is also consistent with our feeling that analysts should use the workflow tools that are best suited to their needs and capabilities.

## A Appendix: Receiving Help for the NlsyLinks Package

A portion of our current grant covers a small, part-time support staff. If you have questions about BG research with our kinship links, or questions about our package, we’d like to hear from you.

We provide personal support for researchers in several ways. Perhaps the best place to start are the forums on R-Forge ([http://r-forge.r-project.org/forum/?group\\_id=1330](http://r-forge.r-project.org/forum/?group_id=1330)); there are forums for people using R, as well as other software such as SAS. [This post](#) is a good overview of the current project is, which originally was an email Joe sent to previous users of our kinship links (many of them are/were SAS users).

## B Appendix: Creating and Saving R Scripts

There are several options and environments for executing R code. Our current recommendation is [RStudio](#), because it is easy to install, and has features targeting beginner and experienced R users. We’ve had good experiences with it on Windows, OS X, and Ubuntu Linux.

RStudio allows you to create and save R files; these are simply text files that have an file extension of ‘.R’. RStudio will execute the commands written in the file. Help documentation for RStudio can be found at <http://www.rstudio.com/ide/docs/>.

## C Appendix: Installing and Loading the NlsyLinks Package

There are three operations you’ll typically do with a package: (a) install, (b) load, and (c) update.

The simplest way to **install** NlsyLinks is to type `install.packages("NlsyLinks")`. You may be asked to select a CRAN mirror to download the package from; if so, choose a close location.

R then will download NlsyLinks on your local computer. It may try to save and install the package to a location that you don't have permission to write files in. If so, R will ask if you would like to install it to a better location (*i.e.*, somewhere you do have permission to write files). Approve this decision (which is acceptable for everyone except for some network administrators).

For a given computer, you'll need to *install* a package only once for each version of R (new versions of R are released every few months). However, you'll need to *load* a package in every session that you call its functions. To **load** NlsyLinks, type either `library(NlsyLinks)` or `require(NlsyLinks)`; (the difference between the two commands is likely irrelevant for most uses.) Loading reads NlsyLinks information from the hard drive and places it in temporary memory. Once it's loaded, you won't need to load it again until R is closed and reopened later.

Developers are continually improving their packages by adding functions and documentation. These newer versions are then uploaded to the CRAN servers. You may **update** all your installed packages at once by typing `update.packages()`. The command checks a CRAN server for newer versions of the packages installed on your local machine. Then they are automatically downloaded and installed.

The grant supporting NlsyLinks extends until Summer 2014. Until then, we'll be including new features and documentation, as we address additional user needs (if you have suggestions, we'd like to hear from you). When the NLSY periodically updates its data, we'll update our kinship links (embedded in NlsyLinks) with the newest information.

## D Appendix: References

A list of some articles that have used the NLSY for behavior genetics is available at: [http://liveoak.github.io/NlsyLinks/research\\_publications.html](http://liveoak.github.io/NlsyLinks/research_publications.html).

Carey, Gregory (2002). *Human Genetics for the Social Sciences*. Sage.

Plomin, Robert (1990). *Nature and nurture: an introduction to human behavioral genetics*. Brooks/Cole Publishing Company.

Rodgers, J. L., Bard, D., Johnson, A., D'Onofrio, B., & Miller, W. B. (2008). *The Cross-Generational Mother-Daughter-Aunt-Niece Design: Establishing Validity of the MDAN Design with NLSY Fertility Variables*. *Behavior Genetics*, 38, 567-578.

Rodgers, Joseph Lee, & Kohler, Hans-Peter (2005). *Reformulating and simplifying the DF analysis model*. *Behavior Genetics*, 35 (2), 211-217.

Rodgers, Joseph Lee, Rowe, David C., & Li, Chengchang (1994). *Beyond nature versus nurture: DF analysis of nonshared influences on problem behaviors*. *Developmental Psychology*, 30 (3), 374-384.

Neale, Michael C., & Cardon, Lou R. (1992). *Methodology for genetic studies of twins and families*. Norwell, MA: Kluwer Academic Publishers. (Also see Neale & Maes: <http://www.vipbg.vcu.edu/OpenMxFall09/NMbook05.pdf>).

## E Notes

This package's development was largely supported by the NIH Grant 1R01HD65865, "NLSY Kinship Links: Reliable and Valid Sibling Identification" (PI: Joe Rodgers; Vignette Construction by Will Beasley)

## F Version Information

- R version 3.5.1 Patched (2018-09-10 r75281), x86\_64-w64-mingw32

- Locale: LC\_COLLATE=English\_United States.1252, LC\_CTYPE=English\_United States.1252, LC\_MONETARY=English\_United States.1252, LC\_NUMERIC=C, LC\_TIME=English\_United States.1252
- Running under: Windows >= 8 x64 (build 9200)
- Matrix products: default
- Base packages: base, datasets, graphics, grDevices, methods, stats, utils
- Other packages: bindrcpp 0.2.2, knitr 1.20, lavaan 0.6-3, magrittr 1.5, NlsyLinks 2.0.8.9000, xtable 1.8-3
- Loaded via a namespace (and not attached): assertthat 0.2.0, backports 1.1.2, bindr 0.1.1, checkmate 1.8.5, colorspace 1.3-2, compiler 3.5.1, crayon 1.3.4, devtools 1.13.6, digest 0.6.18, dplyr 0.7.7, evaluate 0.12, glue 1.3.0, highr 0.7, hms 0.4.2.9001, MASS 7.3-51, memoise 1.1.0, mnormt 1.5-5, munsell 0.5.0, packrat 0.4.9-3, pbivnorm 0.6.0, pillar 1.3.0, pkgconfig 2.0.2, plyr 1.8.4, purrr 0.2.5, R6 2.3.0, Rcpp 0.12.19, readr 1.2.0, rlang 0.2.2, rstudioapi 0.8, scales 1.0.0, stats4 3.5.1, stringi 1.2.4, stringr 1.3.1, tibble 1.4.2, tidyr 0.8.1, tidyselect 0.2.5, tools 3.5.1, withr 2.1.2