

ACE Models with the NLSY

William Howard Beasley (Howard Live Oak LLC, Norman)
Joseph Lee Rodgers (University of Oklahoma, Norman)
Kelly Meredith (University of Oklahoma, Norman)
David Bard (University of Oklahoma Health Sciences Center, OKC)

February 27, 2012

Abstract

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

Contents

1 Terminology	1
2 Example: DF analysis with a Simple Outcome for Gen2 Subjects, Using a Package Variable	2
A Appendix: Creating and Saving R Scripts	4
B Appendix: Installing the NlsyLinks Package	4

`dss`

Not only am I hoping to capitalize on all researchers initially interested in NLSY BG studies, I'm also hoping for a small slice of attracting those that aren't initially interested in BG. If the vignette or articles are good, they should rank well among search engines for terms like "NLSY and R". Maybe some researchers using those terms (and not initially interested in BG) could stumble on the vignettes. If the examples are clear and are easy to run quickly, they may get interested in BG. Therefore, I'd like at least a few paragraphs explaining what BG is. This section is tentatively located in the appendix.

1 Terminology

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 children of the Gen1 females -ie, those in the NLSY79 Children and Young Adults sample (<http://www.bls.gov/nls/nlsy79ch.htm>).

The **SubjectTag** variable uniquely identify NLSY79 subjects when a dataset contains both generations. For Gen2 subjects, the **SubjectTag** is identical to their CID (ie, C00001.00 -the ID assigned in the NLSY79-Children files). However for Gen1 subjects, the **SubjectTag** is their CaseID (ie, 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 variable `R`. Examples are: Monozygotic twins have $R=1$; dizygotic twins have $R=0.5$; full siblings (ie, those who share both biological parents) have $R=0.5$; half-siblings (ie, those who share exactly one biological parent) have $R=0.25$; adopted siblings have $R=0.0$. Other possibilities exist too. The font (and hopefully their context) should distinguish the variable `R` from the software `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 (ie, 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.

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 <http://cran.r-project.org/web/packages/NlsyLinks/>.

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 `CreatePairLinks` function will create a data frame where each represents one pair of siblings. 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 subject `Subject1Tag`, (ii) ID for the younger subject `Subject2Tag`, (iii) ID for their extended family `ExtendedID`, (iv) their coefficient of expected relatedness `R`, (v *and beyond*) outcome values for the older subject; (vi *and beyond*) outcome values for the younger subject.

A DeFries-Fulker (**DF**) Analysis uses linear regression to estimate the h^2 , c^2 , and e^2 of a univariate biometric system. 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 A](#)) and load the `NlsyLinks` package. If you haven't done so, first install the `NlsyLinks` package (see [Appendix B](#)).
3. Within the R script, load the linking dataset. Then select only Gen2 subjects. The 'Pair' version of the linking dataset is essentially a sparse matrix.
4. Load and assign the `ExtraOutcomes79` dataset. Then create the `SubjectTag` variable. We left the `SubjectTag` variable out of the `ExtraOutcomes79` dataset, to demonstrate how to create it; any dataset extracted with the NLS Investigator
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.
6. Create a double-entered file by calling the `CreatePairLinks` function. At minimum, pass the (i) outcome dataset, th (2) raw dataset, and the (iii) name(s) of the outcome variable(s).
7. Use `DeFriesFulkerMethod3` function (i.e., general linear model) to estimate the coefficients of the DF model. The interpretations of the DF analysis can be found in Rodgers, Buster and Rowe (2001).

```
> ### R Code for Example of a DF analysis with a simple outcome and Gen2 subjects
> #Load the package containing the linking routines.
> require(NlsyLinks)
> #
> #Step 3: Load the linking dataset and filter for the Gen2 subjects
> data(Links79Pair)
> dsLinking <- subset(Links79Pair, RelationshipPath=='Gen2Siblings')
> summary(dsLinking)
```

	ExtendedID	Subject1Tag	Subject2Tag	R
Min. :	2	Min. : 201	Min. : 202	Min. : 0.2500
1st Qu.:	3159	1st Qu.: 315901	1st Qu.: 315902	1st Qu.: 0.2500
Median :	6116	Median : 611901	Median : 611902	Median : 0.5000

```

Mean      : 5937      Mean      : 593989      Mean      : 593991      Mean      : 0.4192
3rd Qu.: 8511      3rd Qu.: 851103      3rd Qu.: 851104      3rd Qu.: 0.5000
Max.     :12673     Max.     :1267301     Max.     :1267302     Max.     : 1.0000
                                           NA's     :563.0000

```

```

RelationshipPath
Gen2Siblings:11075

```

```

> #
> #Step 4: Load the outcomes dataset and the linking dataset, and then examine the summary.
> data(ExtraOutcomes79)
> dsOutcomes <- ExtraOutcomes79 #'ds' stands for 'dataset'
> dsOutcomes$SubjectTag <- CreateSubjectTag(dsOutcomes$SubjectID, dsOutcomes$Generation)
> summary(dsOutcomes)

```

```

      SubjectID      Generation MathStandardized      Weight
Min.   :    201   Min.   :2      Min.   : 65.00   Min.   : 75.0
1st Qu.: 310302   1st Qu.:2      1st Qu.: 91.00   1st Qu.: 130.0
Median : 604607   Median :2      Median : 100.00  Median : 155.0
Mean   : 601313   Mean   :2      Mean   : 99.97   Mean   : 161.9
3rd Qu.: 876203   3rd Qu.:2      3rd Qu.: 110.00  3rd Qu.: 186.0
Max.   :1267501   Max.   :2      Max.   : 135.00  Max.   : 485.0
                                           NA's   :2353.00  NA's   :3475.0

```

```

WeightForAge19To25 WeightStandardized WeightStandardizedForAge19To25
Min.   : 75.0      Min.   :-2.768e+00   Min.   :-2.772e+00
1st Qu.: 140.0     1st Qu.:-7.059e-01  1st Qu.:-6.879e-01
Median : 165.0     Median :-2.207e-01  Median :-1.969e-01
Mean   : 172.1     Mean   :-4.252e-11   Mean   :-4.086e-11
3rd Qu.: 195.0     3rd Qu.: 4.739e-01  3rd Qu.: 4.905e-01
Max.   : 485.0     Max.   : 7.178e+00   Max.   : 7.489e+00
NA's   :6380.0     NA's   : 3.475e+03   NA's   : 6.380e+03

```

```

      SubjectTag
Min.   :    201
1st Qu.: 310302
Median : 604607
Mean   : 601313
3rd Qu.: 876203
Max.   :1267501

```

```

> #
> #Step 5: This step isn't necessary for this example, because Kelly Meredith already
> # groomed the values. But if not 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)

```

```

      Subject1Tag      Subject2Tag      ExtendedID      R
Min.   :    201   Min.   :    201   Min.   :    2   Min.   : 0.2500
1st Qu.: 315752   1st Qu.: 315752   1st Qu.: 3158   1st Qu.: 0.2500
Median : 611901   Median : 611901   Median : 6116   Median : 0.5000
Mean   : 593990   Mean   : 593990   Mean   : 5937   Mean   : 0.4192
3rd Qu.: 851104   3rd Qu.: 851104   3rd Qu.: 8511   3rd Qu.: 0.5000
Max.   :1267302   Max.   :1267302   Max.   :12673   Max.   : 1.0000
                                           NA's   :1126.0000

```

```

      RelationshipPath MathStandardized_1 MathStandardized_2
Gen2Siblings:22150  Min.   : 65.00   Min.   : 65.00
                   1st Qu.: 89.00   1st Qu.: 89.00
                   Median : 98.00   Median : 98.00
                   Mean   : 98.29   Mean   : 98.29
                   3rd Qu.: 108.00  3rd Qu.: 108.00
                   Max.   : 135.00  Max.   : 135.00
                   NA's   :3791.00  NA's   :3791.00

> #
> #Step 7: Estimate the ACE components with a DF Analysis
> ace <- DeFriesFulkerMethod3(outcomeForSubject1=dsDouble$MathStandardized_1, outcomeForSubject2=
> ace

$HSquared
[1] 0.8595078
$CSquared
[1] 0.03879863

$RowCount
[1] 16588

```

A Appendix: Creating and Saving R Scripts

bla bla

B Appendix: Installing the NlsyLinks Package

bla bla bla