Metrics

Contents

1 Metrics: labeling factors and exploring scales

Report explains how the response categories from NLSY97 questionnaire are labeled and demonstrates application of labeled factors in data operations and graphing.

1.1 Data In

Initial point of departure - the databox of the selected sample, described in the Methods chapter. This databox corresponds to the dataset **dsL** produced by Derive_dsL_from_Extract report.

```
dsL<-readRDS("./Data/Derived/dsL.rds")
dsL<- dsL[dsL$sample==1,] # cross-sample only
```

1.2 Time metrics : Age, Period, Cohort

NLSY97 sample includes individuals from five cohorts, born between 1980 and 1984.The following graphics shows how birth cohort, age of respondents, and round of observation are related in NSLY97.

There are several indicators of age in NSLY97 that vary in precision. Birth cohort (**byear**) is the most general one, it was recorded once. Two age variables were recorded at each interview: age at the time of the interview in months (**agemon**) and in years (**ageyear**). Those are not derivatives of each other, but are are closely related. The variable **ageyear** records the full number of years a respondent reached at the time of the interview. Due to difficulties of administering the survey, time intervals between the waves could differ. For example, for one person **id** = 25 the age was recorded as 21 years for both 2003 and 2004 (see **ageyear**). However, when you examine age in months (**agemon**) you can see this rounding issue disappears once a more precise scale is used. To avoid this potentially confusing peculiarity, age in years will be calculated as (**age** = **year** - **byear**) or as (**ageALT** = **agemon**/12).

```
ds<-dsL[dsL$year %in% c(2000:2011),c('id',"byear","year","attend","ageyear","agemon")]
ds<- ds[ds$id %in% c(25),]
ds$age<-ds$year-ds$byear
ds$ageALT<- ds$agemon/12
print(ds)
```

```
    id byear year attend ageyear agemon age ageALT
364 25  1983 2000      5      17    214  17  17.83
365 25  1983 2001      7      18    226  18  18.83
366 25  1983 2002      7      19    236  19  19.67
367 25  1983 2003      2      21    254  20  21.17
```

```
368 25  1983 2004      7      21    261  21  21.75
369 25  1983 2005      5      22    272  22  22.67
370 25  1983 2006      7      23    284  23  23.67
371 25  1983 2007      5      24    295  24  24.58
372 25  1983 2008      7      25    307  25  25.58
373 25  1983 2009      7      26    319  26  26.58
374 25  1983 2010      7      27    332  27  27.67
375 25  1983 2011      7      28    342  28  28.50
```

1.3 Mapping Church Attendance

The focal variable of interest is **attend**, an item measuring church attendance in the current year. The questionnaire recorded the responses on the ordinal scale.

Creating frequency distributions for each of the measurement wave we have:

Missing values are used in the calculation of total responses to show the natural attrition in the study. Assumming that attrition is not significantly associated with the outcome measure, we can remove missing values from the calculation of the total of responses and look at percentages that each response was endorsed at each time point.

Graphs above shows change in the cross-sectional distribution of responses over the years. Modeling the change in these response frequencies is handled well by Markov models. LCM, however, works with longitudinal data, modeling the trajectory of each individual and treating attendance as a continuous outcome.

To demonstrate mapping of individual trajectories to time, let's select a dataset that would include personal identifyer (**id**), cohort indicator (**byear**), wave of measurement (**year**) and the focal variable of interest - worship attendance (**attend**).

```r
ds<-dsL[dsL$year %in% c(2000:2011),c('id',"byear","year","attend","attendF")] # select needed variables
print(ds[ds$id==47,])# for a single subject with id=47
```

```
    id byear year attend              attendF
694 47  1982 2000      5    About twice/month
695 47  1982 2001      2        Once or Twice
696 47  1982 2002      4     About once/month
697 47  1982 2003      2        Once or Twice
698 47  1982 2004      3 Less than once/month
699 47  1982 2005      2        Once or Twice
700 47  1982 2006      2        Once or Twice
701 47  1982 2007      3 Less than once/month
702 47  1982 2008      2        Once or Twice
703 47  1982 2009      1                Never
704 47  1982 2010      1                Never
705 47  1982 2011      1                Never
```

The view above lists attendance data for subjust with id = 47. Mapping his attendance to time we have

where vertical dimension maps the outcome value and the horizontal maps the time. There will be a trajecory for each of the

```
cat(length(unique(dsL$id)))
```

```
6748
```

subjects in total. Unless specified otherwise, only individuals from the cross-sample will be used in the model to increase external validity.

```
ds<- dsL[dsL$sample==1,]
```

Each of such trajectories imply a story, a life scenario. Why one person grows in his religious involvement, while other declines, or never develops an interest in the first place? To demostrate how interpretations of trajectories can vary among individuals consider the following scenario.

Attendance trajectories of subjects with **id**s 4, 25, 35, and 47 are plotted in the next graph

```
Warning: Removed 12 rows containing missing values (geom_path).
Warning: Removed 12 rows containing missing values (geom_point).
```

The respondent **id**=35 reported attending no worship services in any of the years, while respodent **id**=25 seemed to frequent it, indicating weekly attendance in 8 out of the 12 years. Individual **id**=47 started as a fairly regular attendee of religious services in 2000 (5= "about twice a month"), then gradually declined his involvement to nill in 2009 and on. Respondent **id**=4, on the other hand started off with a rather passive involvement, reporting attended church only "Once or twice" in 2000, maintained a low level of participation throughout the years, only to surge his attendance in 2011. Latent curve models will describe intraindividual trajectories of change, while summarizinig the interindividual similarities and trends.

Previous research in religiousity indicated that age might be one of the primary factors explaining interindividual differences in church attendance. To examine the role of age, we change the metric of time from waves of measurement, as in the previous graph, to biological age.

```
Warning: Removed 12 rows containing missing values (geom_path).
Warning: Removed 12 rows containing missing values (geom_point).
```

Persons **id** = 35 and **id** = 25 are peers, in 2000 they were both 17. Respondent **id** = 47 is a year older, in 2000 he was 18. The oldest is **id** = 4, who by the last round of measurement in 2011 is 30 years of age. Perhaps, his increased church attendance could be explained by starting a family of his own?

Note that for person **id** = 25 the age was recorded as 21 years for both 2003 and 2004. However, when you examine age in months (**agemon**) you can see this is rounding issue that disappears once a more precise scale is used. To avoid this potentially confusing peculiarity, age in years will be either calculated as (**age** = **year - byear**) or as (**ageALT** = **agemon**/12). See "Mime metrics" section of this report for details.