Psychology 350: Special Topics
An introduction to R for psychological research
Analyzing dynamic data: a tutorial

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https://personality-project.org/courses/350

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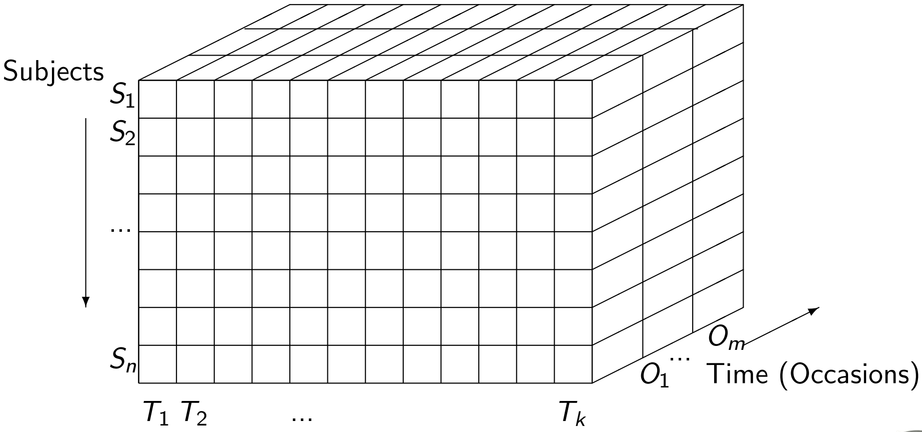
Outline

Dynamic Data: An old problem reconsidered

1. The study of personality has traditionally emphasized how people differ from each other and the reliability and validity of these differences. This has been reflected in the many publications in *Personality and Individual Differences* and others emphasizing the structure of personality, scale construction, and validation.
2. The typical data collected emphasized the "R" approach of Cattell's data box (Cattell, 1946a, 1966a), that is, correlating how participants differ across items/tests.
3. Cattell's data box also included the possibility of studying how one person varied over time ("P"). Sometimes the approach would consider stabilities across time as measured by the correlation of measures taken at two different time points ("S").

The data box: Subjects x Measures x Time



(Cattell, 1946a, 1966b)

Data over time: the long way

1. Studying psychology the "long way" involves longitudinal designs.
2. Traditionally associated with developmental studies, the time periods are years and decades.
3. One of the more impressive stabilities is the correlation of .56 over 79 years of IQ scores from age 11 to age 90 (Deary et al., 2013).
4. An example of what Cattell referred to as a diagonal in his data box would be the correlation across time of individuals taken on different measures.
5. An powerful example of this is the prediction of health related outcomes in middle age from teacher ratings of students in grades 1 - 6 (Hampson and Goldberg, 2006).

Changes in the way data are collected

1. In the past 30 years or so, we have seen an exciting change in the way we collect data, in that we now can study how individuals vary over time (Cattell's P approach). To Cattell, this was "the method for discovering trait unities" (Cattell, 1946b, p 95).
2. The emphasis is now upon individual variability with the added complexity of how these patterns of individual change differ across participants (e.g., Bolger and Laurenceau, 2013; Mehl and Conner, 2012; Wilt et al., 2011, 2016).
3. Although the methods were originally developed to examine data with a nested structure (e.g., students nested within classes nested within schools Bryk and Raudenbush, 1992), the use of these techniques across many occasions within individuals has been labeled *Intensive Longitudinal Methods* (Walls and Schafer, 2006) and "captures life as it is lived" (Bolger et al., 2003).

Dynamic Data

1. We refer to data that show systematic variation over time as dynamic to distinguish them from static cross sectional data (Revelle and Wilt, 2021; Wilt and Revelle, 2022).
2. Formal models that distinguish between dynamic patterns versus stochastic variation (Revelle and Condon, 2015) are beyond the scope of this paper.
3. Although it is possible to examine group patterns over time, it is more typical to consider how individuals differ in their patterning across time.
    - This can be intensive longitudinal (many measures over a short period of time (e.g. multiple measures/day over several weeks) (e.g.,. Fisher et al., 2018; Wilt et al., 2011)
    - More traditional longitudinal (multiple measures taken every year for several years) or
    - Long term longitudinal (life span measures) (e.g., Deary and Batty, 2007; Deary et al., 2013; Terman and Oden, 1947; Lubinski, 2016)

Many names, one analytic tecnique

1. Analytic strategies for analyzing such multi-level data have been given different names in a variety of fields and are known by a number of different terms such as the
    - random effects or random coefficient models of economics,
    - multi-level models of sociology and psychology,
    - hierarchical linear models of education
    - or more generally, mixed effects models (Fox, 2016).
2. Although frequently cautioned not to do so, some psychologists continue to use a repeated measures analysis of variance approaches rather than the more accurate mixed effects models.
3. The *lme4* (Bates et al., 2015) and *nlme* (Pinheiro et al., 2016) packages can do this.

Within groups and between groups

1. The analysis of data at multiple levels presents at least two challenges, one is that of interpretation, the other is that of statistical inference.
2. It has long been known (Yule, 1903) that relationships found within groups are not necessarily the same as those between groups. Although when aggregating across British health districts, it appeared that increased mortality was associated with increases in vaccinations, when examined at the within district level, it was clear that vaccinations reduced mortality (Yule, 1912).
3. Variously known as Simpson's paradox (Simpson, 1951), or the ecological fallacy (Robinson, 1950), the observation is that relationships of aggregated data do not imply the same relationship at the disaggregated level. Such results are examples of non-ergodic relationships, that is, relationships that differ from the individual to the group level (Molenaar,

Structure at different levels of analysis

1. More importantly, when the effect of levels is ignored, structural relationships are difficult to interpret.
2. The correlation between two variables (x and y) when x and y are measured within individuals is a function of the correlation between the individual means ($r_{xy_{between}}$), the pooled within individual correlations ($r_{xy_{wihin}}$) and the relationships between the data and the between group means $\eta_{between}$ as well as the the correlation of the data within the within subject means η_{within}.

$$r_{xy} = \eta_{x_{within}} * \eta_{y_{within}} * r_{xy_{within}} + \eta_{x_{between}} * \eta_{y_{between}} * r_{xy_{between}}. \quad (1)$$

Analyzing dynamic data: a tutorial

1. Revelle and Wilt (2019) work through some examples of analyzing dynamic data.
2. The following slides are taken from that tutorial.
3. Other articles with Josh Wilt discuss why dynamics are some important (Wilt et al., 2011, 2016; Revelle and Wilt, 2021).
4. We first show a "toy" example to see how the functions work
   - Simulate 4 subjects on four variables over six times.
5. Then apply these techniques to an open source data set on emotion (Fisher, 2015).
   - Observed 10 subjects on 27 variables over 100 days

Creating a toy data set

R code

```
library(psych)   #activate the psych package
#create the data
set.seed(42)
x <- sim.multi(n.obs=4,nvar=4,nfact=2,days=6,ntrials=6,plot=TRUE,
          phi.i=c(-.7,0,0,.7),loading=.6)
raw <- round(x[3:8]);   raw[1:4] <- raw[1:4] + 6
#make a 'Fat' version
XFat <- reshape(raw,idvar="id",timevar="time",times=1:4,
    direction="wide")
#show it
XFat

#now make it wide
XWide <- reshape(XFat,idvar="id",varying=2:25,direction="long")
Xwide <- dfOrder(XWide,"id")

#add in the trait information
traits <- data.frame(id = 1:4,extraversion =c(5,10,15,20),
                       neuroticism =c(10,5, 15,10))
Xwide.traits <- merge(Xwide,traits, by ="id")
```

The toy data

R code

```
set.seed(42)
x <- sim.multi(n.obs=4,nvar=4,nfact=2,days=6,ntrials=6,plot=TRUE,
          phi.i=c(-.7,0,0,.7),loading=.6)
raw <- round(x[3:8])
raw[1:4] <- raw[1:4] + 6
headTail(raw,top=8,bottom=8)
```

```
headTail(raw,top=8,bottom=8)
     V1  V2  V3  V4 time  id
1     7  10   4   3   24   1
2     8   7   6   4   48   1
3     8   8   5   2   72   1
4     5   5   5   6   96   1
5     8   8   5   5  120   1
6    11   9   1   2  144   1
7     6   6   6   5   24   2
8     7   8   5   5   48   2
...  ... ... ... ...  ... ...
17    4   4   6   7  120   3
18    5   4   7   7  144   3
19    4   5   4   4   24   4
20    6   4   4   5   48   4
21    5   7   5   6   72   4
22    3   4   5   5   96   4
23    5   4   4   3  120   4
24    5   4   4   5  144   4
```

Show the wide data set

R code

```
XFat <- reshape(raw,idvar="id",timevar="time",times=1:4,
    direction="wide")
#show it
XFat
```

```
XFat
   id V1.24 V2.24 V3.24 V4.24 V1.48 V2.48 V3.48 V4.48 V1.72 V2.72 V3.72
1   1     7    10     4     3     8     7     6     4     8     8     5
7   2     6     6     6     5     7     8     5     5     7     7     6
13  3     5     6     4     4     6     5     5     4     5     6     6
19  4     4     5     4     4     6     4     4     5     5     7     5
   V4.72 V1.96 V2.96 V3.96 V4.96 V1.120 V2.120 V3.120 V4.120 V1.144 V2.144
1      2     5     5     5     6      8      8      5      5     11      9
7      7     7     7     6     6      7      7      4      4      8      7
13     7     6     6     9     6      4      4      6      7      5      4
19     6     3     4     5     5      5      4      4      3      5      4
   V3.144 V4.144
1       1      2
7       6      6
13      7      7
19      4      5
```

Add the personality variables to it

R code

```
#now make it wide
XWide <- reshape(XFat,idvar="id",varying=2:25,direction="long")
Xwide <- dfOrder(XWide,"id")
#add in the trait information
traits <- data.frame(id = 1:4,extraversion =c(5,10,15,20),
                     neuroticism =c(10,5, 15,10))
Xwide.traits <- merge(Xwide,traits, by ="id")
```

```
headTail(Xwide.traits,top=8,bottom=8)
     id time  V1  V2  V3  V4 extraversion neuroticism
1     1   24   7  10   4   3            5          10
2     1   48   8   7   6   4            5          10
3     1   72   8   8   5   2            5          10
4     1   96   5   5   5   6            5          10
5     1  120   8   8   5   5            5          10
6     1  144  11   9   1   2            5          10
7     2   24   6   6   6   5           10           5
8     2   48   7   8   5   5           10           5
... ...  ... ... ... ... ...          ...         ...
17    3  120   4   4   6   7           15          15
18    3  144   5   4   7   7           15          15
19    4   24   4   5   4   4           20          10
20    4   48   6   4   4   5           20          10
21    4   72   5   7   5   6           20          10
22    4   96   3   4   5   5           20          10
23    4  120   5   4   4   3           20          10
24    4  144   5   4   4   5           20          10
```

Always describe the data

R code

```
describe(Xwide.traits)
```

```
describe(Xwide.traits)
             vars  n  mean    sd median trimmed   mad min max range  skew kurtosis   se
id              1 24  2.50  1.14    2.5    2.50  1.48   1   4     3  0.00    -1.49 0.23
V1              2 24  6.17  1.74    6.0    6.10  1.48   3  11     8  0.61     0.44 0.35
V2              3 24  6.17  1.74    6.0    6.05  1.48   4  10     6  0.28    -0.91 0.35
V3              4 24  5.08  1.47    5.0    5.05  1.48   1   9     8 -0.06     1.81 0.30
V4              5 24  4.92  1.50    5.0    5.00  1.48   2   7     5 -0.31    -0.89 0.31
time            6 24 84.00 41.87   84.0   84.00 53.37  24 144   120  0.00    -1.41 8.55
extraversion    7 24 12.50  5.71   12.5   12.50  7.41   5  20    15  0.00    -1.49 1.17
neuroticism     8 24 10.00  3.61   10.0   10.00  3.71   5  15    10  0.00    -1.16 0.74
>
```

And show the correlations

R code

```
lowerCor(Xwide.traits)
```

```
             id    V1    V2    V3    V4    time  extrv nrtcs
id            1.00
V1           -0.75  1.00
V2           -0.75  0.77  1.00
V3            0.05 -0.28 -0.21  1.00
V4            0.25 -0.43 -0.38  0.67  1.00
time          0.00  0.16 -0.17  0.00  0.20  1.00
extraversion  1.00 -0.75 -0.75  0.05  0.25  0.00  1.00
neuroticism   0.32 -0.38 -0.38  0.16  0.08  0.00  0.32  1.00
```

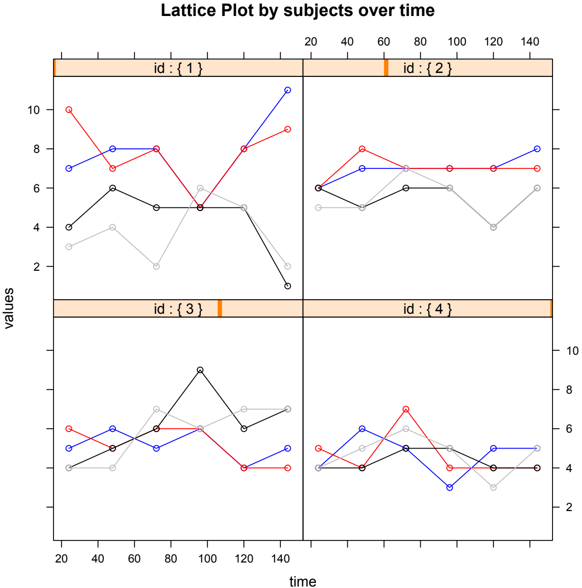
Display the data using `mlPlot`.

`mlPlot` is a simple helper function to call some *lattice* plotting routines.

R code

```
mlPlot(Xwide.traits, grp = "id", Time = "time", items = c(2:5),
+    col=c("blue","red","black","grey"),
+     main="Lattice Plot by subjects over time")
```

A toy data set



How did it do this?

Examine mlPlot (revised 5/02/23)

R code

```
mlPlot
```

```
mlPlot
function (x, grp = "id", Time = "time", items = c(3:5), extra = NULL,
    col = c("blue", "red", "black", "grey"),type="b", main = "Lattice Plot by subjects over t
    ...)
{
    long <- mlArrange(x = x, grp = grp, Time = Time, items = items,
        extra = extra)
    plot1 <- xyplot(values ~ time | id, group = items, data = long,
        type = type, as.table = TRUE, strip = strip.custom(strip.names = TRUE,
            strip.levels = TRUE), col = col, main = main, ...)
    print(plot1)
    invisible(long)
}
<bytecode: 0x1580c58a8>
<environment: namespace:psych>
```

Open and shared science

1. One of the more powerful uses of the web is to share data
2. A number of data sets are available for other people to use
3. Aaron Fisher at UCB has released a data set of positive and negative mood for 10 subjects over 100 days (Fisher, 2015)
4. Other, larger data sets, are also available.

The Fisher data set

1. Although available on the web, it is necessary to download the data and do some rearrangements to make it useful for our purposes.
2. In a study of 10 participants diagnosed with clinically generalized anxiety disorder, (Fisher, 2015) collected 28 items for at least 60 days per participant.
3. I have moved this data set to the 350 folder so that we can use it more readily.
4. In an impressive demonstration of how different people are, he examined the dynamic factor structure of each person using procedures discussed by Molenaar (1985).

The table of contents of fisher data

```
personality-project/courses/350/Fisher_2015_Data/P030/
 personality-project/courses/350/Fisher_2015_Data/P065/
 personality-project/courses/350/Fisher_2015_Data/P009/
 personality-project/courses/350/Fisher_2015_Data/P007/
 personality-project/courses/350/Fisher_2015_Data/P022/
 personality-project/courses/350/Fisher_2015_Data/P013/
 personality-project/courses/350/Fisher_2015_Data/P023/
 personality-project/courses/350/Fisher_2015_Data/P002/
 personality-project/courses/350/Fisher_2015_Data/P010/
 personality-project/courses/350/Fisher_2015_Data/P011/
```

Each subfolder contains a number of files, including an RData file. We want to read each of these files and then combine them. We create a small function `combine.data` to do this.

Using the Fisher data set

R code

```
"combine.data" <- function(dir=NULL,names,filename=NULL) {
  new <- NULL
  n <- length(names)
  old.dir <- getwd()   #save the current working directory
for (subject in 1:n) {  #repeat n times, once for each subject
if(is.null(filename)) {setwd(dir)}  else {dir <- filename}
  #set the working directory to where the files are
  #this is specific to this particular data structure
  x <- read.file(f=paste0(dir,"/P",names[subject],"/pre",
           names[subject],".csv"))
  nx <- nrow(x)
   #add id and time to this data frame
  temp <- data.frame(id=names[subject],time=1:nx,x)
   #combine with prior data.frames to make a longer object
  new <- rbind(new,temp)
   }  #end of the subject loop
 setwd(old.dir)   #set the working directory back to the original
 return(new)}   #end the function by returning the data
```

```
folder.name <- "http://personality-project.org/courses/350/Fisher_2015_Data/Fisher_2015_data"
```

Use this function

R code

```
names <- c("002","007","009","010","011","013","022","023",
        "030","065")  #hard coded from his file names
         #specify where the data are
filename <-
  "http://personality-project.org/courses/350/Fisher_2015_Data"
new <- combine.data(dir=NULL, names=names,filename=filename)
dim(new)
```

```
dim(new)
[1] 792  29

 colnames(new)
 [1] "id"         "time"        "happy"      "sad"        "angry"
 [6] "content"    "afraid"      "lonely"     "relaxed"    "tired"
[11] "anxious"    "positive"    "percent"    "interfere"  "upset"
[16] "wcontent"   "tension"     "difficult"  "control"    "concentrate"
[21] "mustens"    "fatigue"     "irritable"  "sleep"      "restless"
[26] "avoid"      "prepare"     "procrast"   "reassur"
```

As with any data set, first we describe it

R code
```
describe(new)
```

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
id*	1	792	5.27	2.90	5.0	5.21	2.97	1	10	9	0.17	-1.25	0.10
time	2	792	41.34	25.36	40.0	40.15	29.65	1	118	117	0.42	-0.31	0.90
happy	3	788	156.44	316.53	38.0	70.51	26.69	3	999	996	2.27	3.20	11.28
sad	4	788	148.20	319.72	29.0	61.04	31.13	0	999	999	2.27	3.19	11.39
angry	5	788	148.61	319.41	30.0	61.44	28.17	1	999	998	2.27	3.20	11.38
content	6	788	154.26	317.46	33.0	67.99	26.69	3	999	996	2.27	3.19	11.31
afraid	7	788	152.49	318.28	36.0	66.33	37.06	0	999	999	2.26	3.18	11.34
lonely	8	788	151.39	318.66	36.0	65.07	37.06	0	999	999	2.27	3.18	11.35
relaxed	9	788	152.97	317.78	30.0	66.36	19.27	2	999	997	2.27	3.20	11.32
tired	10	788	167.59	312.62	55.0	84.41	35.58	1	999	998	2.26	3.18	11.14
anxious	11	788	170.52	311.44	62.5	87.98	30.39	0	999	999	2.27	3.19	11.09
positive	12	788	158.27	315.89	41.0	72.74	31.13	3	999	996	2.27	3.20	11.25
percent	13	788	170.42	315.02	57.0	87.27	32.62	4	999	995	2.23	3.03	11.22
interfere	14	788	168.30	315.96	52.5	84.92	34.84	0	999	999	2.23	3.03	11.26
upset	15	788	170.76	313.10	56.0	87.49	32.62	6	999	993	2.25	3.11	11.15
wcontent	16	788	171.13	314.70	56.5	87.92	30.39	3	999	996	2.23	3.04	11.21
tension	17	788	170.10	313.37	60.0	86.97	31.13	4	999	995	2.25	3.11	11.16
difficult	18	788	172.06	314.41	58.0	89.25	31.13	2	999	997	2.23	3.03	11.20
control	19	788	171.82	314.50	59.0	88.88	31.13	3	999	996	2.23	3.03	11.20
concentrate	20	788	164.91	318.81	46.0	80.71	29.65	4	999	995	2.22	2.97	11.36
mustens	21	788	167.25	318.19	53.0	83.88	40.03	0	999	999	2.21	2.95	11.34
fatigue	22	788	171.17	316.65	52.0	88.30	35.58	4	999	995	2.21	2.95	11.28
irritable	23	788	166.52	318.18	47.0	82.59	26.69	2	999	997	2.22	2.97	11.33
sleep	24	788	169.42	317.51	50.0	86.41	40.03	3	999	996	2.21	2.94	11.31
restless	25	788	171.13	316.51	53.0	88.02	32.62	3	999	996	2.22	2.96	11.28
avoid	26	788	166.69	318.65	45.0	83.20	37.06	0	999	999	2.21	2.93	11.35
prepare	27	788	165.72	318.94	44.0	82.09	37.06	0	999	999	2.21	2.94	11.36
procrast	28	788	168.61	317.98	45.5	85.53	39.29	3	999	996	2.20	2.93	11.33

We need to clean up the data to get rid of missing values

R code

```
fisher <- scrub(new, max=101)
#But that messes up the id field
fisher <- scrub(new, where =2:29, max = 120)
#id field is quasi numeric
table(fisher$id)
fisher$id <- as.numeric(fisher$id) #keeps the original values
describe(fisher)
```

```
fisher <- scrub(new, where =2:29, max = 120)
> describe(fisher)
id            1 792 18.53 17.28     11   14.85  5.93   2  65    63  1.78     2.31 0.61
time          2 792 41.34 25.36     40   40.15 29.65   1 118   117  0.42    -0.31 0.90
happy         3 691 38.16 21.69     33   36.37 20.76   3  97    94  0.67    -0.49 0.82
sad           4 691 28.77 23.42     21   26.02 22.24   0 100   100  0.83    -0.17 0.89
angry         5 691 29.23 20.72     25   26.99 22.24   1 100    99  0.89     0.38 0.79
content       6 691 35.68 23.52     28   33.15 20.76   3 100    97  0.81    -0.45 0.89
afraid        7 691 33.66 25.77     29   31.01 29.65   0 100   100  0.67    -0.53 0.98
lonely        8 691 32.40 25.35     28   29.80 31.13   0 100   100  0.65    -0.49 0.96
relaxed       9 691 34.21 20.89     28   31.85 14.83   2  93    91  0.97     0.11 0.79
tired        10 691 50.88 25.55     50   51.03 31.13   1 100    99 -0.03    -1.07 0.97
anxious      11 691 54.22 24.37     57   55.20 26.69   0 100   100 -0.31    -0.84 0.93
positive     12 691 40.25 22.31     38   38.73 25.20   3 100    97  0.51    -0.71 0.85
percent      13 689 51.36 23.13     50   50.98 29.65   4 100    96  0.12    -0.96 0.88
interfere    14 689 48.94 25.18     45   48.21 29.65   0  99    99  0.22    -1.18 0.96
upset        15 690 53.13 23.36     50   52.87 29.65   6 100    94  0.09    -1.05 0.89
wcontent     16 689 52.18 22.35     50   51.67 25.20   3 100    97  0.16    -0.83 0.85
tension      17 690 52.37 23.67     51   52.77 31.13   4 100    96 -0.11    -1.20 0.90
difficult    18 689 53.24 23.17     51   53.16 28.17   2 100    98  0.00    -0.94 0.88
control      19 689 52.96 23.19     51   52.73 28.17   3 100    97  0.05    -0.96 0.88
```

Fisher's data: pooled across subjects

R code

```
positive <- cs(happy,content,relaxed, positive)
negative <- cs(angry,afraid, sad, lonely)
pana <- c(positive,negative)  #we want to select the items
R <- lowerCor(fisher[pana])  #to show in a correlation matrix
pana.scores <- scoreItems(keys=list(positive=positive,
         negative=negative), fisher, impute="median")
summary(pana.scores)
```

```
         happy cntnt relxd postv angry afrad sad   lonly
happy     1.00
content   0.80  1.00
relaxed   0.67  0.74  1.00
positive  0.84  0.79  0.70  1.00
angry    -0.19 -0.15 -0.12 -0.15  1.00
afraid   -0.36 -0.37 -0.28 -0.34  0.65  1.00
sad      -0.34 -0.32 -0.23 -0.31  0.67  0.75  1.00
lonely   -0.24 -0.21 -0.12 -0.21  0.64  0.74  0.80  1.00


Scale intercorrelations corrected for attenuation
 raw correlations below the diagonal, (unstandardized) alpha on the diagonal
 corrected correlations above the diagonal:
        positive negative
positive     0.93    -0.33
negative    -0.30     0.91
```

Fisher affect over time

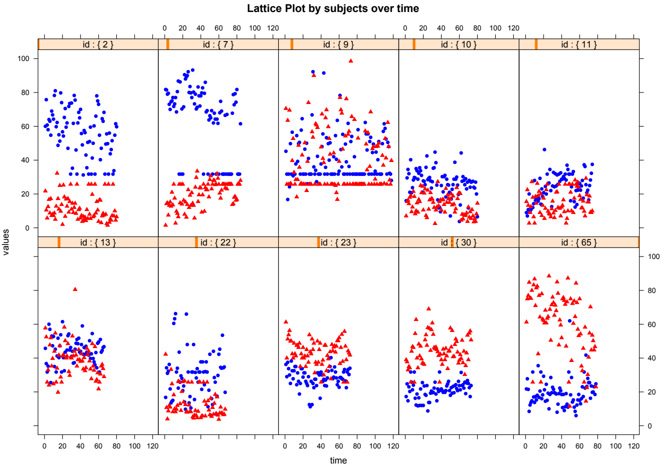
R code

```
affect.df <-cbind(fisher[1:2], pana.scores$score)
describe(affect.df)
lowerCor(affect.df)
```

```
 describe(affect.df)
        vars   n  mean    sd median trimmed   mad  min    max range skew kurtosis   se
id         1 792 18.42 17.37  11.00   14.85  5.93 1.00  65.00  64.0 1.75     2.25 0.62
time       2 792 41.34 25.36  40.00   40.15 29.65 1.00 118.00 117.0 0.42    -0.31 0.90
positive   3 792 36.40 18.76  31.75   34.39 15.57 3.75  93.25  89.5 0.94     0.20 0.67
negative   4 792 30.34 19.79  25.75   28.41 21.50 1.50  98.50  97.0 0.75    -0.07 0.70
> lowerCor(affect.df)
        id    time  postv negtv
id       1.00
time    -0.08  1.00
positive -0.50  0.01  1.00
negative  0.60 -0.01 -0.30  1.00
```

Fisher's data, measuring positive and negative affect over time

```
mlPlot(fisher,type="p",items=3:4,col=c("blue","red"),pch= c(16,17))
```



Fisher's affect data within subjects over time

R code

```
sb.affect<- statsBy(affect.df,"id",cors=TRUE)
round(sb.affect$within,2)
round(sb.affect$pooled,2)
sb.affect
```

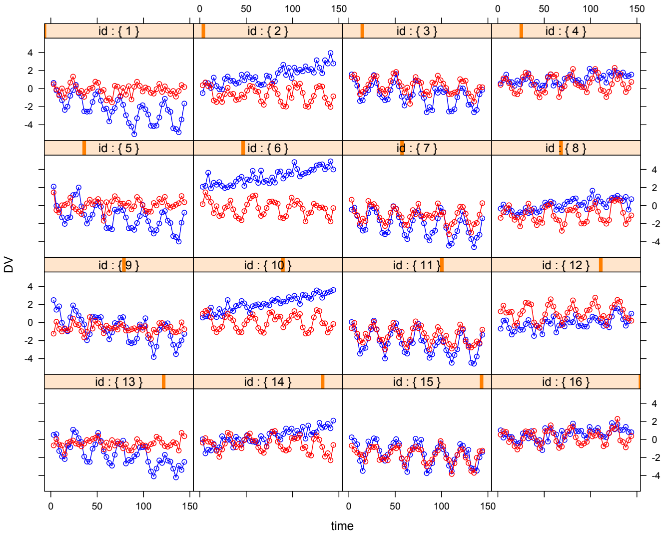
```
 time-postv time-negtv postv-negtv
1        -0.38      -0.18       -0.36
7        -0.48       0.53       -0.60
9         0.05      -0.03        0.35
10       -0.29      -0.36       -0.28
11        0.43       0.13       -0.28
13        0.03      -0.22       -0.05
22       -0.04      -0.32       -0.24
23       -0.01      -0.22       -0.16
30        0.29       0.11       -0.43
65        0.09      -0.48       -0.74

         time positive negative
time      1.00    -0.04    -0.10
positive -0.04     1.00    -0.29
negative -0.10    -0.29     1.00
sb.affect
Statistics within and between groups
Call: statsBy(data = affect.df, group = "id", cors = TRUE)
Intraclass Correlation 1 (Percentage of variance due to groups)
      id     time positive negative
    1.00     0.10     0.64     0.70
Intraclass Correlation 2 (Reliability of group differences)
      id     time positive negative
    1.00     0.90     0.99     0.99
```

Simulating data

To understand how models work, it useful to simulate data where we know the structure. `sim.multi` does this.

1. Trends over time
2. Diurnal variation
3. Within subject variability
4. `sim.multi()` defaults to 4 subjects for two variables over 16 days.

Simulated data over time



Conclusion

Modern data collection techniques allow for intensive measurement within subjects. Analyzing this type of data requires analyzing data at the within subject as well as between subject level. Although sometimes conclusions will be the same at both levels, it is frequently the case that examining within subject data will show much more complex patterns of results than when they are simply aggregated. This tutorial is a simple introduction to the kind of data analytic strategies that are possible.
(See http://personality-project.org/courses/350/350.wk7b.html for worked examples.)
These slides have been adapted from (Revelle and Wilt, 2019): Analyzing dynamic data: a tutorial

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