Tutorial of network analyses of ESM data: the lagnetw package

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Abstract

Network analyses have many applications. In this tutorial we focus on networks build with data obtained with the experience sampling method (ESM). The networks are directed, the relations between the variables in the network are directed because lagged predictors are used. An arrow in the network represents an effect from a variable measured at t-1 on another variable measured at t or on itself measured at t.

In this tutorial we will show how the package “lagnetw” can be used to do a network analysis.

Keywords: network ESM lags Multilevel

Tutorial of network analyses of ESM data: the lagnetw package

Introduction

For this tutorial a network is defined as a visual representation of a set of variables together with the relations between these variables. The aim of such a network is to better understand the underlying process, which has realized the measurements on the variables. etc. etc. Examples of the network approach in personality research are in (Costantini et al., 2015). Other papers discuss the psychological networks and their accuracy (Epskamp, Borsboom, & Fried, 2018) and controversial issues related to networks for psychopathology (Bringmann & Eronen, 2018).

The `lagnetw` is in the R package `lagnetw`. This package can be installed from Github and then loaded using the `library()` function:

```
devtools::install_github("PeterVerboon/lagnetw")
```

```r
library(lagnetw)
```

ESM

short about what and why of ESM data

Building a Network

There are many ways to construct a network of psychological variables [refs]. For instance, a network can simply build from the correlation matrix using the `qgraph` package [Epstein]. Here, we demonstrate the multilevel regression approach with lagged variables. The general idea is that we estimate for each variable measured at time t, the strengh of the effect of all the other variables on it, where the predictors are measured at time t-1.The effects of a predictor on a given variable, say y(t), is controlled for by all other predictors, including the given variable measured at t-1 (y(t-1)). The represented effects in the network are therefore partial effects. This network is similar to networks based on a correlation matrix, in which the lines between variables also represent partial correlations.

$$y_j(t) = b_{j0} + \sum_{k=1}^{M} b_{jk} y_k(t-1) + e_j. \tag{1}$$

where j = 1,..,M and k = 1,..,M. When there are M variables for which we want to build a network, there are also M predictors for each variable. After running the analyses the regression coefficients are gathered in a square matrix. The diagonal of this matrix represents the effects of y(t-1) on y(t), controlled for the other predictors. Since ESM data are hierarchical, the measurements are clustered within days and within subjects. To deal with possible cluster effects of subjects, the regression model shown in formula (1) is extended to a multilevel model in which the intercepts and slopes are allowed to vary across individuals (see formula (2))

$$\begin{aligned} y_{ij}(t) = b_{ij0} + \sum_{k=1}^{M} b_{ijk} y_{ik}(t-1) + e_{ij} \\ b_{ij0} = b_{j0} + u_{ij0} \\ b_{ijk} = b_{jk} + u_{ijk}. \end{aligned} \tag{2}$$

Example

To illustrate how a network can be build, we start with an example. The data for this example (DataNews) were obtained in an ESM study about the effect of daily news perceptions on mood fluctuations (De Hoog & Verboon, 2019). During 10 days, and at 7 random moments per day, participants indicated whether they had perceived news, and if they had, to rate the valence of the news, using 5 variables. After having scored the news they had to rate their mood using items from the PANAS. First, some helpful objects for the analysis were constructed. After selecting a relevant subset of the data for this example, we constructed an object `vars`, which cobtained the variable names that were used to build the network. To label the variables in the network plot with convenient symbols, we can define labels, which we added in the object `labs`. Furthermore, groups of variables are defined and set in the object `varGroups`. Variables belonging to each other are placed in the same group. Here we have variables that refer to the news, which indicate the subjective valence of the news (the Valence group), and we have mood items, put in the group called “Affect”.

```
data("news")

vars <- c("Fearful","Hopeful","Anxious","Down","Inspiring","Irritated","Relaxed","Insecu
labs <- c("Fear","Hope","Anx", "Down","Insp","Irri","Relax","Insec")
varGroups <- list(Valence = c(1,2,5), Affect = c(3,4,6,7,8))

res <- esmNetwork(dat=news,
                subjnr="subjnr",
                level2 = "daynr",
                level1 = "beepnr",
                vars = vars,
                covs = c("age"),
                randomAll = FALSE,
                randomVars =  c("Fearful","Hopeful","Inspiring"),
                randomIcept = TRUE,
                fixedIcept = TRUE,
                layout = "spring",
```

```
                lagn = 1,
                centerType = c("grand_mean"),
                groups = varGroups,
                plimit = 0.10,
                solid = 0.10,
                titlePlot = NULL,
                labs = labs)
```

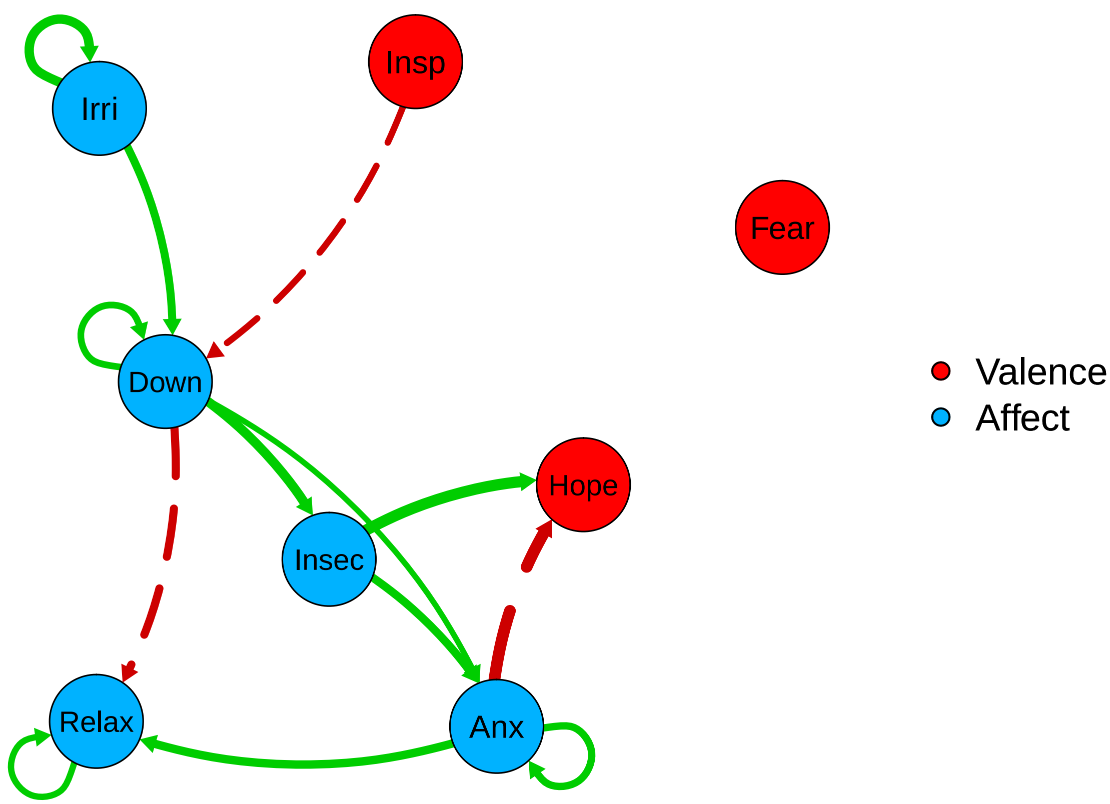

Figure 1

The function ‘esmNetwork()’ is used to run the analyses and build a network based on these analyses. The function assumes ESM data or a similar structure. That means that we assume there are persons (subjects), who have answered a short questionnaires several times a day, during several days. The intermediate level (days) is not necessary, and could be absent. The lagged analyses are defined on the first level, the measurements within days (beeps). The number of lags can be varied with “lagn=”, but this will usually be set to 1, the default value.

In the function call “vars” is a vector with variable names, which are used to build the netword. The relevant variables can either be grand-mean centered or centered within groups, which is pseciﬁed with “centerType”. The centerType option can be a single term (“grand-mean” or “person”) or a vector, which has the same length as “vars”, and which speciﬁes for each variable the type of centering. After “covs=” the covariates are speciﬁed, which are used in all analyses as covariates, but never as dependent variables, so they are not plotted in the network. In the multilevel models all variables can be deﬁned as random eﬀects by setting “randomAll=” to true. This means that their slopes are estimated as random eﬀects. Also, a subset of the variables can be speciﬁed as random eﬀects, using “randomVars=”. The intercept is usally estimated as foxed and random eﬀect, but this can be chnaged by the settin gthe parameters “ﬁxedIcept” and “randomIcept” to FALSE. The layout parameter takes care for the general layout of the ﬁgure. More details can be found in the documentation of the qgraph function. The “groups” parameter speciﬁes if diﬀerent groups get a diﬀerent coulour in the ﬁgure. The variable labels for the ﬁgure can be speciﬁed in the “labs” parameter. Furthermore, plmit and solid determine which arrows are drawn in the ﬁgure. Finally, a title can be provided.

With the plot command the plot is drawn in the plots window, as follows.

```
plot(res$output$network)
```

Indices of centrality

To better understand the role of the variables in the network several statistics for a network have been developped, which are called indices of centrality.

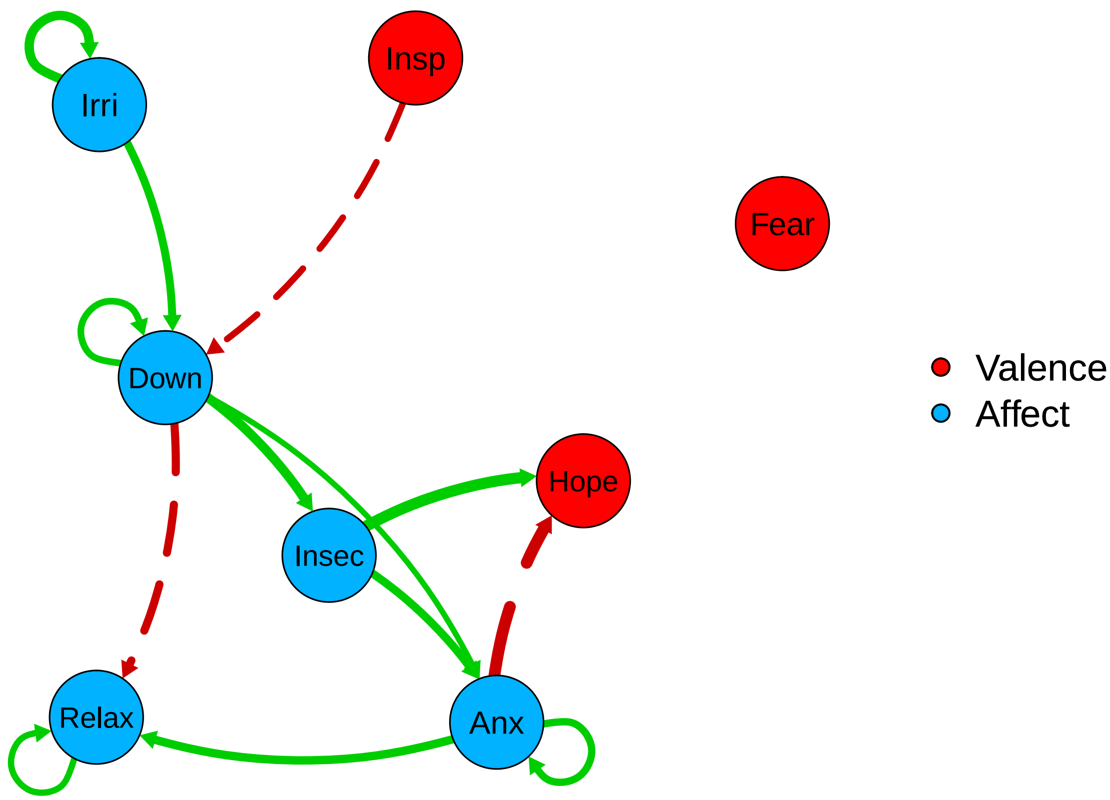

Figure 2

Note

We used R (Version 3.5.1; R Core Team, 2018) and the R-packages *lagnetw* (Version 0.1.4; Verboon, 2019), and *papaja* (Version 0.1.0.9842; Aust & Barth, 2018) for all our analyses.

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