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Stability and variability of personality networks. A tutorial on recent developments in network psychometrics

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ABSTRACT

Networks have been recently proposed for modeling dynamics in several kinds of psychological phenomena, such as personality and psychopathology. In this work, we introduce techniques that allow disentangling *between-subject* networks, which encode dynamics that involve stable individual differences, from *within-subject* networks, which encode dynamics that involve momentary levels of certain individual characteristics. Furthermore, we show how networks can be simultaneously estimated in separate groups of individuals, using a technique called the Fused Graphical Lasso. This technique allows also performing meaningful comparisons among groups. The unique properties of each kind of network are discussed. A tutorial to implement these techniques in the "R" statistical software is presented, together with an example of application.

Networks allow representing complex phenomena in terms of a set of elements that interact with each other. Networks include two basic components, the nodes, which represent the elements of a system, and the edges, that connect nodes and represent their pairwise interactions. Networks have been recently proposed as a model of complex psychological phenomena such as individual differences in psychopathology (Borsboom & Cramer, 2013; Schmittmann et al., 2013) and personality (Costantini, Epskamp, et al., 2015; Costantini & Perugini, 2016b; Cramer et al., 2012). From the network perspective, broad patterns of individual differences in both normal personality and psychopathology can be conceptualized as phenomena that emerge from the interactions among certain behaviors, cognitions, motivations, and emotions. For example, individual differences in depression could arise from, and could be maintained by, vicious cycles of mutual relationships among symptoms. A depression symptom such as insomnia can cause another symptom, such as fatigue, which in turn can determine concentration problems and worrying, which can result in more insomnia and so on (Borsboom & Cramer, 2013; Fried & Cramer, 2017). Similarly, broad personality traits such as conscientiousness and extraversion in the network perspective are not seen as explanations of basic individual differences, such as the time an individual spends attending parties and her number of friends (McCrae & Costa, 2008). Instead, individual differences in broad personality traits are considered phenomena to explain in terms of dynamic interactions. For instance, a researcher could focus on the fact that people who like to go to parties tend to meet more people and therefore to gain more friends, people who have more friends get invited to parties more often, and so on (Cramer et al., 2012). In this way, networks provide an explanation of individual differences that connects their structure to potential underlying processes and dynamics (Baumert et al., 2017).

The growing interest in conceptualizing individual differences in dynamic terms has led research to use intensive longitudinal data (Walls & Schafer, 2006), that is, many repeated measurements for multiple persons. Examples of intensive longitudinal data research designs include diary reports, observational methods, and ecological momentary assessment (EMA; Trull & Ebner-Priemer, 2013), which have become highly feasible and efficient thanks to the widespread use of electronic devices such as tablets and smartphones. The defining characteristics of these methods are that the assessment is both ecological (i.e., experiences are measured in the participant's natural environment) and momentary (i.e., assessment captures information about immediate or near immediate experiences and requires minimal retrospection; Shiffman, Stone, & Hufford, 2008).

In this work, we provide a primer on both established and new methods for computing and analyzing networks in psychology and investigating individual differences (e.g., in personality and psychopathology) and their patterns of stability and variability in two main ways. First, individual differences, for instance in personality characteristics, have been shown to vary around a stable central tendency according to the characteristics of the occasion (Fleeson, 2001). For example, it has been shown that individuals, independent of their typical level of extraversion, act in a more extraverted way when their goal is to be at the center of attention and in a less extraverted way when they want

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to "recharge their batteries" (McCabe & Fleeson, 2016). We present both techniques that allow analyzing dynamics involving the stable component of individual differences and techniques that allow investigating the dynamics characterizing the transient variability among different occasions. Focusing on stable between-subject differences is particularly relevant if one is interested in the dynamics that involve one individual's typical levels of a trait, whereas if one's interest is in the dynamics that involve the momentary level of certain characteristics in individuals, one should focus on the variability between occasions (Epskamp, Waldorp, Mõttus, & Borsboom, 2017).

Second, individual differences and their dynamics can vary among groups. One could be interested in inspecting which dynamics are similar and which vary across individuals, for example who are addicted to different substances (Rhemtulla et al., 2016), who follow different types of psychotherapy (Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015), who are diagnosed with a disorder or not (Richetin, Preti, Costantini, & De Panfilis, 2017) or who live in different countries (Costantini & Perugini, 2017). In psychopathology, this issue has been referred to as heterogeneity (Fried & Cramer, 2017; Mõttus et al., 2015). We present new techniques that allow simultaneously estimating networks from different groups of individuals and identifying patterns of similarities and differences in the dynamics characterizing these groups (Danaher, Wang, & Witten, 2014). Such methods allow inspecting whether between-subject and between-occasion dynamics are stable or vary among groups.

Once a network is computed, network analysis offers a powerful toolbox to summarize complex patterns of relationships. For instance, network analysis allows analyzing the global structural organization, or topology, of a phenomenon (e.g., Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011; Costantini et al., 2015) or the role played by specific elements of the network, such as by identifying the most "central" or "peripheral" elements of a system (Costantini, Epskamp, et al., 2015; Freeman, 1978). In this work, we will introduce the most important network indices and show how they can be computed in R (R Core Team, 2017).

1. Estimating and analyzing networks in psychology

When investigating personality, nodes can represent symptoms (Borsboom & Cramer, 2013), behaviors, emotions, cognitions, and motivations that can vary across individuals or occasions. Nodes can be assessed by single items in questionnaires (Cramer et al., 2012) or by aggregates of items, for instance personality facets (Costantini & Perugini, 2016b). The choice of an appropriate level of investigation (e.g., items, facets, or even broader traits) depends on which level is most useful for investigating the phenomenon of interest (Costantini & Perugini, 2012).

Edges represent pairwise connections between nodes and can be characterized by three main properties: *weight*, *sign*, and *direction*. Weights encode information about the intensity of the relationships and are graphically represented by the thickness of the lines connecting the nodes. Signs allow distinguishing positive from negative relationships and are conventionally represented by colors: green (or blue) edges are positive and red edges are negative. For personality and psychopathology research, edge weights and signs are fundamental, because they allow distinguishing between intense and weak and between positive and negative associations among variables (Costantini & Perugini, 2014). Edge direction allows representing asymmetrical relationships between nodes and is typically represented by arrowheads. Edge direction has been used in psychology particularly for representing temporal dependencies (Bringmann et al., 2013, 2016, 2015).

The interpretation of the edges crucially depends on the method used for computing the network. In turn, not all methods can be applied to all kinds of datasets. Examples of sources of data in psychology include participants' rating on an object of interest (e.g., themselves, a peer, or a situation) collected only once (cross-sectional studies) or many times (e.g., as in EMA studies). Whereas networks can be computed both on cross-sectional and longitudinal datasets, disentangling the variation due to subjects (i.e., to their stable central tendency) from the variation due to the specific occasion requires repeated-measure data (Epskamp, Waldorp, et al., 2017). Moreover, group comparisons can be performed only if participants can be univocally assigned to different groups.

1.1. Estimating networks on cross-sectional data

Although correlation networks can be used (e.g., Cramer et al., 2012), the most common method for cross-sectional data has been to elaborate partial correlation networks (Costantini, Epskamp, et al., 2015; Epskamp, Borsboom, & Fried, 2017), which are equivalent to standardized Gaussian Graphical Models (GGM; Lauritzen, 1996; for a detailed presentation of the GGM in psychology, see Epskamp et al., 2017). In partial correlation networks, an edge between any two nodes is drawn if they correlate after controlling for all other variables in the network. The absence of an edge in partial correlation networks (i.e., a zero in the partial correlation matrix) indicates that two nodes are conditionally independent given the others, and therefore is particularly informative (Lauritzen, 1996). However, because exact zeros cannot be easily observed in sample partial correlation matrices and because in partial correlation networks an increase in the number of nodes can lead to overfitting and very unstable estimates (Babyak, 2004), such networks are usually estimated using regularization methods such as the least absolute shrinkage and selection operator (*lasso*; Tibshirani, 1996).

Partial correlations can be computed from the concentration (or precision) matrix, which is the inverse of the correlation matrix, via simple mathematical operations.[1] The *graphical lasso* (glasso) methodology estimates a concentration matrix by imposing a lasso regularization directly on its elements[2]: Instead of estimating the concentration matrix by maximizing the log-likelihood function, the glasso maximizes a penalized log-likelihood, the penalty being equal to the sum of the absolute values of the elements of the concentration matrix, multiplied by a tuning parameter λ_1 (Friedman, Hastie, & Tibshirani, 2008). The larger is the value of λ_1, the stronger is the penalization and the sparser will be the estimated concentration matrix (with many zero coefficients). The λ_1 parameter therefore regulates the sparsity of the resulting network: By setting the λ_1 parameter to zero (i.e., no regularization), one simply gets the maximum likelihood estimates of the partial correlations. Established ways to select a value for the tuning parameter include selection according to an information criterion, such as the Extended BIC (EBIC; Chen & Chen, 2008; Epskamp, 2016; Foygel & Drton, 2010), or via cross-validation (e.g., Krämer, Schäfer, & Boulesteix, 2009). This method has been widely used in psychology[3] (e.g., Beard et al., 2016; Isvoranu et al., 2017; van Borkulo et al., 2015) and, compared to the maximum likelihood estimates of partial correlations, it improves both the accuracy and the interpretability of the results (Tibshirani, 1996), especially if the sparsity of the model matches that of the true data-generating network (Epskamp, Kruis, & Marsman, 2016).

[1] A partial correlation matrix can be computed by standardizing the concentration matrix (each element of the matrix is divided by the square root of the product of the corresponding diagonal elements) and by computing the opposite of the resulting off-diagonal elements (the formula can be found for instance in Lauritzen, 1996, p. 130).

[2] The exact formula of the graphical lasso and the details of the fitting algorithm can be found in the original work by Friedman and colleagues (Friedman et al., 2008).

[3] Other methods for computing a regularized partial correlation matrix are also available (e.g., Krämer et al., 2009; Meinshausen & Bühlmann, 2006). However, in this work we focus exclusively on the glasso, which is more flexible, since it takes as input a correlation matrix instead of the whole dataset. For this reason, the glasso handles ordinal data better, because a polychoric variance-covariance matrix can be used as input (Epskamp, Borsboom, et al., 2017). Furthermore, the glasso has been extended to the case of multiple groups (Danaher et al., 2014; Guo et al., 2011).