Chapter 10

State of the aRt Personality Research

Abstract

Network analysis represents a novel theoretical approach to personality. Network approaches motivate alternative ways of analyzing data, and suggest new ways of modeling and simulating personality processes. In the present chapter, we provide an overview of network analysis strategies as they apply to personality data. We discuss different ways to construct networks from typical personality data, and show how to compute and interpret important measures of centrality and clustering. All analyses are illustrated using a data set on the commonly used HEXACO questionnaire using elementary R-code that readers may easily adapt to apply to their own data.

10.1 Introduction

A network is an abstract model composed of a set of nodes or vertices, a set of edges, links or ties that connect the nodes, together with information concerning the nature of the nodes and edges (e.g., De Nooy, Mrvar, & Batagelj, 2011). Figure 10.1 reports the example of a simple network, with six nodes and seven edges. The nodes usually represent entities and the edges represent their relations. This simple model can be used to describe many kinds of phenomena, such as social relations, technological and biological structures, and information networks (e.g., Newman, 2010, Chapters 2–5). Recently networks of relations among thoughts, feelings and behaviors have been proposed as models of personality and of psychopathology: in this framework, traits have been conceived of as emerging

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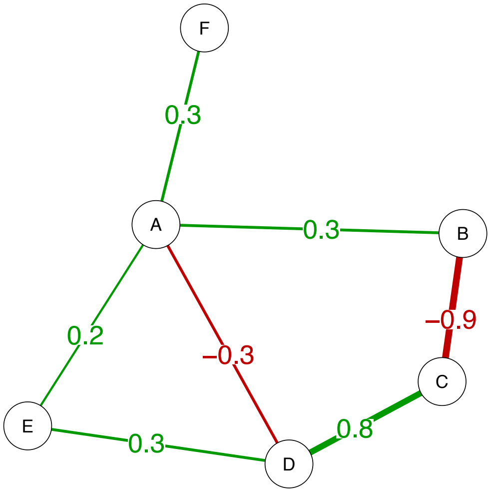

Figure 10.1: A network with six nodes and seven edges. Positive edges are green and negative edges are red. The letters identify the nodes, the numbers represent weights associated to the edges

phenomena that arise from such networks (Borsboom & Cramer, 2013; Cramer, Sluis, et al., 2012; Schmittmann et al., 2013). An R package, *qgraph*, has been developed for the specific purpose of analyzing personality and psychopathology data (Epskamp et al., 2012).

The aim of this contribution is to provide the reader with the necessary theoretical and methodological tools to analyze personality data using network analysis, by presenting key network concepts, instructions for applying them in R (R Core Team, 2016), and examples based on simulated and on real data. First, we show how a network can be defined from personality data. Second, we present a brief overview of important network concepts. Then, we discuss how network concepts can be applied to personality data using R. In the last part of the chapter, we outline how network-based simulations can be performed that are specifically relevant for personality psychology. Both the data and the R code are available for the reader to replicate our analyses and to perform similar analyses on his/her own data.

10.2 Constructing Personality Networks

A typical personality data set consists of cross-sectional measures of multiple subjects on a set of items designed to measure several facets of personality. In standard approaches in personality research, such data are used in factor analysis to search for an underlying set of latent variables that can explain the structural covariation in the data. In a causal interpretation of latent variables (Borsboom et al., 2003), responses to items such as "I like to go to parties" and "I have many friends" are viewed as being causally dependent on a latent variable (e.g., extraversion). For example, McCrae and Costa's (2008) interpretation of the relation between extraversion and its indicators is explicitly causal: "extraversion causes party-going behavior in individuals" (McCrae & Costa, 2008, p. 288). This approach has culminated in currently influential models such as the Five Factor Model of personality (McCrae & Costa, 2008), in which five dominant latent variables are ultimately held responsible for most of the structural covariation between responses to personality items (additional latent factors such as facets may cause some of the covariation).

Recently, however, this perspective has been challenged in the literature (Cramer, Sluis, et al., 2012). In particular, it has been put forward that the default reliance on latent variable models in personality may be inappropriate, because it may well be that the bulk of the structural covariation in personality scales results from direct interactions between the variables measured through personality items. For instance, one may suppose that people who like to go to parties gain more friends because they meet more people, and people who have more friends get invited to good parties more often. In this way, one can achieve an explanation of the relevant pattern of covariation without having to posit latent variables.

Thus, in this scheme of thinking, one may suppose that, instead of reflecting the pervasive influence of personality factors, the structural covariance in personality is actually due to local interactions between the variables measured. In this way of thinking, personality resembles an ecosystem in which some characteristics and behaviors stimulate each other, while others have inhibitory relations. Under this assumption, the proper way to analyze personality data is not through the a priori imposition of a latent variable structure, but through the construction of a network that represents the most important relations between variables; this way, one may get a hold of the structure of the ecosystem of personality.

It is important to stress that not all personality scholars have embraced a causal view of latent factors. Some researchers for instance consider factors as the common elements shared by many observable variables and not as their causes (Ashton & Lee, 2005; Funder, 1991; Lee, 2012). Also from this different theoretical perspective, the heuristic value of network analysis remains important. Factor and network analysis differ, at the very least, in the fact that they direct the researcher's attention toward different aspects of personality. While factor analysis focuses almost exclusively on the elements shared among the indicators, whether or not interpreted causally, network analysis shifts the focus towards the direct relationships among the observable variables. We do not challenge the use of factor analysis as a statistical technique by itself: network analysis and factor analysis can in principle be combined (Cramer, Sluis, et al., 2012; Lee, 2012)[1]. However, a network perspective may foster important insights in the field that are unlikely to come by relying exclusively on a latent variable perspective.

The current section explains how a network structure can be estimated and visualized in R based on typical personality research data. We explain how networks

[1]See also Chapter 7 and Chapter 8 for recent discussions on this topic.

are encoded in weights matrices, discuss the most important kinds of networks and show how to estimate these network.

Directed and Undirected Networks

There are different types of networks, which yield different kinds of information and are useful in different situations. In a *directed* network, relationships between nodes are asymmetrical. Research on directed networks has seen extensive developments in recent years since the work of Pearl and Verma (1995) and others on causal systems. Methodology based on directed networks is most useful if one is willing to accept that the network under consideration is *acyclic*, which means that there are no feedback loops in the system (if A influences B, then B cannot influence A). A directed network without feedback loops is called a Directed Acyclic Graph (DAG). In contrast, in an *undirected* network, all relationships are symmetrical. These networks are most useful in situations where (a) one cannot make the strong assumption that the data-generating model is a DAG, (b) one suspects that some of the relations between elements in the network are reciprocal, and (c) one's research is of an exploratory character and is mainly oriented to visualizing the salient relations between nodes. Since the latter situation appears more realistic for personality research, the current chapter focuses primarily on undirected networks.

Encoding a Network in a Weights Matrix

The structure of a network depends on the relations between its elements. *Unweighted* networks represent only the presence or absence of the edges, while *weighted* networks encode additional information about the magnitude of the connections. When it is important to distinguish large from small connections—such as in personality—weighted networks are preferred. A weighted network can be encoded in a *weights matrix*, which is a square matrix in which each row and column indicate a node in the network. The elements of the matrix indicate the strength of connection between two nodes; a zero in row i and column j indicates that there is no edge between node i and node j. For example, the network of Figure 10.1 can be represented with the following weights matrix:

	A	B	C	D	E	F
A	0	0.3	0	-0.3	0.2	0.3
B	0.3	0	-0.9	0	0	0
C	0	-0.9	0	0.8	0	0
D	-0.3	0	0.8	0	0.3	0
E	0.2	0	0	0.3	0	0
F	0.3	0	0	0	0	0

In this network there are positive connections, for instance between nodes A and B, and negative connections, for instance between nodes A and D. The zeroes in the matrix indicate that there are absent connections in the network, such as between nodes A and C. Furthermore, we may note that the matrix is symmetric and that the diagonal values are not used in the network.

The *qgraph* package (Epskamp et al., 2012) can be used to visualize such a weights matrix as a network:

```
mat <- matrix(c(
   0,  0.3,    0, -0.3,  0.2, 0.3,
 0.3,    0, -0.9,    0,    0,   0,
   0, -0.9,    0,  0.8,    0,   0,
-0.3,    0,  0.8,    0,  0.3,   0,
 0.2,    0,    0,  0.3,    0,   0,
 0.3,    0,    0,    0,    0,   0), ncol = 6, nrow = 6,
byrow = TRUE)

library("qgraph")

qgraph(mat, layout = "spring", edge.labels = TRUE,
  labels = LETTERS[1:6], fade = FALSE)
```

Here, the first argument in the `qgraph` function—the (`mat`) argument—calls the weights matrix to plot. The other arguments specify graphical layout.

Correlation Networks, Partial Correlation Networks, and LASSO Networks

To illustrate network analysis on personality data we made public a dataset in which nine-hundred-sixty-four participants (704 female and 256 male, M age = 21.1, SD = 4.9, plus four participants who did not indicate gender and age) were administered the HEXACO-60 (Ashton & Lee, 2009). The HEXACO-60 is a short 60-items inventory that assesses six major dimensions of personality: honesty-humility, emotionality, extraversion, Agreeableness vs. anger, conscientiousness and openness to experience (Ashton & Lee, 2007). Each of the major dimensions subsumes four facets, which can be computed as the average of two or three items. Participants indicated their agreement with each statement on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*). An example of an item (of trait emotionality) is "When I suffer from a painful experience, I need someone to make me feel comfortable".

We can load the HEXACO dataset into R as follows:

```
Data <- read.csv("HEXACOfacet.csv")
```

The reader may use `str(Data)` to get an overview of the variables in the dataset. Exploratory factor analysis can be performed to inspect the structure of the dataset, using package psych (Revelle, 2010). The command `fa.parallel(Data)` executes parallel analysis, which suggests six factors. The command `fa(r=Data, nfactors=6, rotate="Varimax")` can be used to extract six orthogonal factors. Factor loadings are reported in Table 10.1 and reproduce the expected structure

	E	C	O	X	H	A	Uniq.	Compl.	Smc
Hsi	-.05	.11	.11	.05	**.60**	-.05	.61	1.17	.26
Hfa	.14	.22	.15	-.04	**.63**	.19	.48	1.69	.39
Hga	.11	-.01	.24	.03	**.54**	.14	.62	1.65	.29
Hmo	.04	-.01	.05	-.05	**.44**	.07	.79	1.12	.16
Efe	**.48**	.03	-.16	-.22	-.07	-.04	.69	1.72	.27
Ean	**.55**	.17	.08	-.12	.11	-.11	.63	1.54	.30
Ede	**.66**	-.01	-.11	-.08	-.01	-.03	.55	1.10	.34
Ese	**.68**	.07	.02	.10	.13	.08	.50	1.18	.36
Xss	-.36	.18	.06	**.53**	-.08	.00	.54	2.14	.38
Xsb	-.05	.08	.07	**.63**	-.02	-.25	.52	1.40	.36
Xso	.17	-.02	.03	**.65**	.06	.01	.55	1.17	.33
Xli	-.11	.06	.02	**.67**	.00	.12	.52	1.13	.37
Afo	.09	-.09	.04	.13	.16	**.43**	.75	1.68	.20
Age	.09	-.06	-.02	.04	.13	**.54**	.68	1.21	.23
Afl	-.06	-.02	-.01	-.10	.06	**.67**	.53	1.08	.29
Apa	-.11	.10	.14	-.01	.09	**.49**	.71	1.45	.22
Cor	.01	**.73**	-.07	.06	.01	.00	.46	1.03	.37
Cdi	.19	**.58**	.19	.21	.18	-.03	.51	1.99	.41
Cpe	.08	**.70**	.18	.05	.06	-.08	.46	1.22	.41
Cpr	-.21	**.52**	.12	-.12	.15	.12	.62	1.87	.32
Oaa	-.04	.17	**.71**	-.04	.15	.04	.44	1.23	.42
Oin	-.25	.09	**.59**	.04	.15	-.01	.56	1.55	.35
Ocr	.15	.01	**.62**	.14	.01	.08	.56	1.26	.32
Oun	-.07	.01	**.57**	.10	.11	-.08	.65	1.22	.29

Table 10.1: Factor loadings. Factors are labeled according to their highest loadings. Note: E = loading on emotionality, C = loading on conscientiousness, O = loading on openness to experience, X = loading on extraversion, H = loading on honesty-humility, A = loading on agreeableness versus anger. Smc = squared multiple correlation of each facet with all the others. Uniq. = uniqueness. Compl. = Hofmann's row-complexity index (1978).

(Ashton & Lee, 2009). For each facet Table 10.1 reports also the squared multiple correlation with all the other facets and the Hofmann's row-complexity index, which represents the number of latent variables needed to account for each manifest variable (Hofmann, 1978; Pettersson & Turkheimer, 2010) and is included in the output of function `fa`.

Correlation networks. We will construct networks by representing measured variables as nodes, connected by an edge if two variables interact with each other. To do this we can use a simple heuristic: node A is connected to node B if node A *is associated with* node B. A correlation matrix describes pairwise associations between the facets of the HEXACO and therefore can be used for estimating such a network structure. We can compute Pearson correlations on this dataset using the `cor` function:

```
cor(Data)
```

Notice that a correlation matrix is symmetric and that a value of zero indicates no connection. Thus, a correlation matrix, by default, has properties that allow it to be used as a weights matrix to encode an undirected network. Using this connection opens up the possibility to investigate correlation matrices visually as networks. To do so, we can use the *qgraph* package and ask it to plot the correlation matrix as a network; in the remainder, we will indicate this network as a *correlation network*. To facilitate interpretation, we color nodes according to the assignment of facets to traits as specified in the HEXACO manual:

```
groups <- factor(c(
    rep("Honesty Humility", 4),
    rep("Emotionality", 4),
    rep("Extraversion", 4),
    rep("Agreeableness vs. anger", 4),
    rep("Conscientiousness", 4),
    rep("Openness to experience", 4)))

qgraph(cor(Data), layout = "spring", labels = colnames(Data),
groups = groups)
```

Figure 10.2A represents the correlation structure of the facets of the HEXACO dataset. Green lines represent positive correlations, while red lines represent negative correlations. The wider and more saturated an edge is drawn, the stronger the correlation. As the reader may expect, the figure shows that the correlations of facets within traits are generally higher than the correlations of facets between traits, which is likely to reflect the fact that in psychometric practice items are typically grouped and selected on the basis of convergent and discriminant validity (Campbell & Fiske, 1959).

In recent literature correlation networks have been applied to grasp complex co-variation patterns in personality data that would be harder to notice otherwise in, say, factor loading matrices. Epskamp et al. (2012) showed how *qgraph* can be used to visualize the correlational structure of a 240 node dataset (Dolan et al., 2009) in which the NEO-PI-R (Costa & McCrae, 1992; Hoekstra et al., 2003) was used to assess the five factor model for personality (McCrae & Costa, 2008). Cramer, Sluis, et al. (2012) further analyzed this network and showed that it did not correspond to a correlation network that should arise had the data been generated by the five factor model for personality. Ziegler et al. (2013) constructed a correlation network on 113 personality facet scale scores from the NEO-PI-R, HEXACO, 6FPQ, 16PF, MPQ, and JPI and interpreted this network as a nomological network usable in scale development. Schlegel, Grandjean, and Scherer (2013) investigated the overlap of social and emotional effectiveness constructs and found the correlation network to display four meaningful components. Finally, Franić, Borsboom, Dolan, and Boomsma (2014) used correlation networks to show the similarity between genetic and environmental covariation between items of the NEO-FFI.

Partial correlation networks. Correlation networks are highly useful to visualize interesting patterns in the data that might otherwise be very hard to spot. However, they are not necessarily optimal for the application of network analysis if the goal is to extract the structure of a data-generating network. The reason is that correlations between nodes in the network may be spurious, rather than being due to a genuine interaction between two nodes. For instance, spurious correlations may arise as the consequence of shared connections with a third node. Often, therefore, a network is constructed using the partial correlation matrix, which gives the association that is left between any two variables after conditioning on all other variables. The partial correlation coefficients are directly related to the inverse of the correlation matrix, also called the precision matrix (Lauritzen, 1996; Pourahmadi, 2011). Networks constructed on this basis are called *partial correlation networks* or *concentration graphs* (Cox & Wermuth, 1993), and the statistical data-generating structures that they encode are known as Markov random fields (Kindermann, Snell, et al., 1980).

The partial correlation network can be obtained in *qgraph* by setting the argument `graph` to `"concentration"`:

```
qgraph(cor(Data), layout = "spring", labels = colnames(Data),
groups = groups, graph = "concentration")
```

The partial correlation network is shown in Figure 10.2B. We can see that nodes still cluster together; the partial correlations within traits are generally stronger than the partial correlations between traits. Comparing figures 2A and 2B we can see structure emerging in for example the Openess (purple) cluster: the creativity node (Ocr) is no longer directly connected to the inquisitiveness (Oin) and unconventionality (Oun) nodes but now indirectly via the aesthetic appreciation (Oaa) node. Furthermore, we can see that the conscientiousness node prudence (Cpr) now has a more central role in the network and obtained relatively stronger connections with nodes of different traits: flexibility (Afl) and patience (Apa) of the Agreeableness vs. anger trait and sociability (Xso) and Social self-esteem (Xss) of the extroversion trait.

Adaptive LASSO networks. In weighted networks, two nodes are connected if and only if the strength of connection between them is nonzero; a value of zero in the weights matrix encodes no connection between two nodes. Both the correlation and the partial correlation networks have been estimated based on an empirical sample and will therefore not result in exact zeroes. Thus, both networks will always be fully connected networks, possibly with arbitrarily small weights on many of the edges.

It has been argued that in social sciences everything is to some extent correlated with everything. This is akin to what Meehl and Lykken have called the *crud factor* or *ambient noise level* (Lykken, 1968, 1991; Meehl, 1990) and what may at least partly be responsible for the controversial general factor of personality (Musek, 2007). If a network model of pairwise interactions is assumed to underlie the data then all nodes that are indirectly connected will be correlated, mainly due to spurious connections. Therefore, even at the population level we can assume

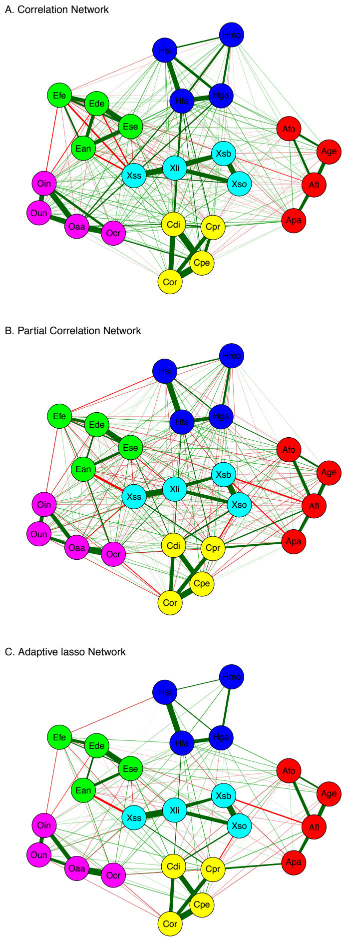

Figure 10.2: Networks of the HEXACO-60. Nodes represent personality facets (a description of each facet is provided in Table 10.2), green lines represent positive connections and red lines represent negative connections. Thicker lines represent stronger connections and thinner lines represent weaker connections. The node placement of all graphs is based on the adaptive LASSO network to facilitate comparison. The width and color are scaled to the strongest edge and not comparable between graphs; edge strengths in the correlation network are generally stronger than edge strengths in the partial correlation network.

that most correlations in personality research will be nonzero, resulting in a fully connected correlation network.

While correlation networks of personality measures are likely to be fully connected in the population, partial correlation networks are not necessarily so. This is of specific interest since the absence of an edge in a partial correlation network entails that two nodes are conditionally independent given all other nodes in the network—they cannot directly interact. The model in which partial correlations are set to zero is called the Gaussian graphical model (GGM; Lauritzen, 1996) as it can be visualized as a network. An optimal GGM is both sparse (many absent edges) while maintaining a high likelihood. Finding such a model corresponds to checking which connections are absent in the population network. Default significance tests can be used for this purpose (Drton & Perlman, 2004). However, significance tests require an arbitrary choice of significance level; different choices yield different results, with more stringent significance levels resulting in sparser networks. If one ignores this issue, one has a multiple testing problem, whereas if one deals with it in standard ways (e.g., through a Bonferroni correction), one faces a loss of power.

A practical way to deal with the issue of arbitrary choices is to construct networks based on different choices and to see how stable the main results are; however, a more principled alternative is to use a LASSO penalty (Friedman, Hastie, & Tibshirani, 2008) in estimating the partial correlation networks. This causes small connections to automatically shrink to be exactly zero and results in a parsimonious network. If the data indeed arose from a sparse network with pairwise interactions, such a procedure will in fact converge on the generating network (Foygel & Drton, 2011).

The adaptive LASSO is a generalization of the LASSO that assigns different penalty weights for different coefficients (Zou, 2006) and outperforms the LASSO in the estimation of partial correlation networks, especially if the underlying network is sparse (Fan, Feng, & Wu, 2009; Krämer et al., 2009). The penalty weights can be chosen in a data-dependent manner, relying on the LASSO regression coefficients (Krämer et al., 2009). In simulation studies, the likelihood of false positives using this method resulted even smaller than that obtained with the LASSO penalization (Krämer et al., 2009), so if an edge is present in the adaptive LASSO network one can reasonably trust that there is a structural relation between the variables in question (of course, the network does not specify the exact nature of the relation, which may for instance be due to a direct causal effect, a logical relation pertaining to item content, a reciprocal effect, or the common effect of an unmodeled latent variable).

The adaptive LASSO is also convenient practically, as it is implemented in the R-package *parcor* (Krämer et al., 2009). Since the adaptive LASSO, as implemented in package parcor, relies on k-fold validation, `set.seed` can be used to ensure the exact replicability of the results, which might be slightly different otherwise. To estimate the network structure of the HEXACO dataset according to the adaptive LASSO, the following code can be used:

```
library("parcor")
library("Matrix")
```

```
set.seed(100)
adls <- adalasso.net(Data)
network <- as.matrix(forceSymmetric(adls$pcor.adalasso))
qgraph(network, layout = "spring", labels = colnames(Data),
groups = groups)
```

The adaptive LASSO network is shown in Figure 10.2C. One can see that, compared to the partial correlation network, the adaptive LASSO yields a more parsimonious graph (fewer connections) that encodes only the most important relations in the data; In this network 134 (48.6%) of the edges are identified as zero.

10.3 Analyzing the Structure of Personality Networks

Once a network is estimated, several indices can be computed that convey information about network structure[2]. Two types of structure are important. First, one is typically interested in the *global* structure of the network: how large is it? Does it feature strong clusters? Does it reveal a specific type of structure, like a small-world (Watts & Strogatz, 1998)? Second, one may be interested in *local* patterns, i.e., one may want to know how nodes differ in various characteristics: which nodes are most central? Which nodes are specifically strongly connected? What is the shortest path from node A to node B? Here we discuss a limited selection of indices that we regard as relevant to personality research, focusing especially on centrality and clustering coefficients. More extensive reviews of network indices may be found in Boccaletti et al. (2006); Butts (2008); de De Nooy et al. (2011); Kolaczyk (2009); and Newman (2010).

Descriptive Statistics

Before the computation of centrality measures, a number of preparatory computations on the data are in order. The network is undirected, therefore the corresponding weights matrix is symmetric and each edge weight is represented twice, above and below the main diagonal. The function `upper.tri` can be used to extract the unique edge weights[3] and save them in a vector:

```
ew <- network[upper.tri(network)]
```

To compute the number of edges in the network, it is sufficient to define a logical vector that has value `TRUE` (= 1) if the edge is different from zero and `FALSE` (

[2]The adaptive LASSO networks, the correlation and the partial correlation networks are characterized by the presence of both positive and negative edges. The importance of signed networks is apparent not only in the study of social phenomena, in which it is important to make a distinction between liking and disliking relationships (e.g., Leskovec, Huttenlocher, & Kleinberg, 2010), but also in the study of personality psychology (e.g., Costantini & Perugini, 2014). Some network indices have been generalized to the signed case (e.g., Costantini & Perugini, 2014; Kunegis, Lommatzsch, & Bauckhage, 2009), however most indices are designed to unsigned networks. For the computation of the latter kind of indices, we will consider the edge weights in absolute value.

[3]The function `upper.tri` extracts the elements above the main diagonal. One could equally consider those below the diagonal using the function `lower.tri`.

= 0) if the edge is exactly zero (i.e., absent). The sum of this vector gives the number of nonzero edges. With a similar procedure, it is possible to count the positive and the negative edges: it is sufficient to replace `!=` with `>` or `<`:

```
sum(ew != 0) # the number of edges
sum(ew > 0) # the number of positive edges
sum(ew < 0) # the number of negative edges
```

The network has 142 edges, of which 100 are positive and 42 are negative. The function t.test can be used to compare the absolute weights of the positive versus the negative edges:

```
t.test(abs (ew [ew > 0]), abs(ew [ew < 0]) , var.equal = TRUE)
```

In our network, positive edges are generally associated to larger weights (M = .11, SD = .09) than the negative edges (M = .06, SD = .04), and the t-test indicates that this difference is significant, t(140) = 3.13, p = .0022.

Centrality Measures

Not all nodes in a network are equally important in determining the network's structure and, if processes run on the network, in determining its dynamic characteristics (Kolaczyk, 2009). Centrality indices can be conceived of as operationalizations of a node's importance, which are based on the pattern of the connections in which the node of interest plays a role. In network analysis, centrality indices are used to model or predict several network processes, such as the amount of flow that traverses a node or the tolerance of the network to the removal of selected nodes (Borgatti, 2005; Crucitti, Latora, Marchiori, & Rapisarda, 2004; Jeong, Mason, Barabási, & Oltvai, 2001) and can constitute a guide for network interventions (Valente, 2012). Several indices of centrality have been proposed, based on different models of the processes that characterize the network and on a different conception of what makes a node important (Borgatti & Everett, 2006; Borgatti, 2005) The following gives a succinct overview of the most often used centrality measures[4].

Degree and strength. First, degree centrality is arguably the most common centrality index and it is defined as the number of connections incident to the node of interest (Freeman, 1978). The degree centrality of node C in Figure 10.1 is 2 because it has two connections, with nodes B and D. Degree can be straightforwardly generalized to weighted networks by considering the sum of the weights of the connections (in absolute value), instead of their number. This generalization is called *strength* (Barrat, Barthelemy, Pastor-Satorras, & Vespignani, 2004; Newman, 2004). For instance, strength of node C in Figure 10.1 is 1.7, which is

[4]The functions to implement centrality indices, clustering coefficients and small-worldness are implemented in the R package *qgraph* (Epskamp et al., 2012). Some of the functions rely on procedures originally implemented in packages *igraph* (Csardi & Nepusz, 2006), *sna* (Butts, 2010), and *WGCNA* (Langfelder & Horvath, 2012). These packages are in our experience among the most useful for network analysis.

the highest in the network. Degree and strength focus only on the paths of unitary length (Borgatti, 2005). A strength-central personality characteristic (e.g., an item, a facet or a trait) is one that can influence many other personality characteristics (or be influenced by them) directly, without considering the mediating role of other nodes.

Closeness and betweenness. Several other measures exist that, differently from degree centrality and the related indices, consider edges beyond those incident to the focal node. An important class of these indices rely on the concepts of *distance* and of *geodesics* (Brandes, 2001; Dijkstra, 1959). The distance between two nodes is defined as the length of the shortest path between them. Since, in typical applications in personality psychology, weights represent the importance of an edge, weights are first converted to lengths, usually by taking the inverse of the absolute weight (Brandes, 2008; Opsahl et al., 2010). The *geodesics* between two nodes are the paths that connect them that have the shortest distance. *Closeness centrality* (Freeman, 1978; Sabidussi, 1966) is defined as the inverse of the sum of the distances of the focal node from all the other nodes in the network[5]. In terms of network flow, closeness can be interpreted as the expected speed of arrival of something flowing through the network (Borgatti, 2005). A closeness-central personality characteristic is one that is likely to be quickly affected by changes in another personality characteristic, directly or through the changes in other personality features. Its influence can reach other personality features more quickly than the influence of those that are peripheral according to closeness, because of the short paths that connect itself and the other traits. In the network in Figure 10.1, node D has the highest closeness. To compute the exact value of closeness, one should first compute the distances between D and all the other nodes: A ($1/0.3$), B ($1/0.8 + 1/0.9$), C ($1/0.8$), E ($1/0.3$) and F ($1/.3 + 1/.3$). The sum of all the distances is 16.94 and the inverse, 0.59, is the closeness centrality of D.

Betweenness centrality is defined as the number of the geodesics between any two nodes that pass through the focal one. To account for the possibility of several geodesics between two nodes, if two geodesics exist, each one is counted as a half path and similarly for three or more (Brandes, 2001; Freeman, 1978). Betweenness centrality assumes that shortest paths are particularly important (Borgatti, 2005): if a node high in betweenness centrality is removed, the distances among other nodes will generally increase. Both closeness and betweenness centrality can be applied to weighted and directed networks, as long as the weights and/or the directions of the edges are taken into account when computing the shortest paths (e.g., Opsahl et al., 2010).

The betweenness centrality of node A in Figure 10.1 is 4 and is the highest in the network. The four shortest paths that pass through A are those between F and the nodes B, C, D, and E. Betweenness centrality can also be extended to evaluate the centrality of edges instead of nodes, by considering the geodesics

[5]The computation of closeness assumes that the network is connected (i.e., a path exists between any two nodes), otherwise, being the distance of disconnected nodes infinite, the index will result to zero for all the nodes. Variations of closeness centrality that address this issue have been proposed (Kolaczyk, 2009; Opsahl et al., 2010). Alternatively it can be computed only for the largest component of the network (Opsahl et al., 2010).

that pass through an edge: this generalization is called *edge betweenness centrality* (Brandes, 2008; Newman, 2004; Newman & Girvan, 2004). For instance, the edge-betweenness centrality of the edge (D,E) is 3 and the three shortest paths that pass through (D,E) are the one between D and E, the one between C and E (through D), and the between B and E (through C and D).

Betweenness-central personality characteristics and betweenness-central edges are particularly important for other personality characteristics to quickly influence each other. It is interesting to investigate the conditions in which some nodes become more or less central. For instance, a study that analyzed a network of moods showed that the mood "worrying" played a more central role for individuals high in neuroticism than for those with low neuroticism (Bringmann et al., 2013): the prominent role of worrying for neuroticism was recently confirmed by an experimental fMRI study (Servaas, Riese, Ormel, & Aleman, 2014).

Brandes (2008) discusses several other variants of the shortest-paths betweenness, some of which are implemented in package *sna* (Butts et al., 2008). Generalizations of betweenness centrality that account for paths other than the shortest ones have been also proposed (Brandes & Fleischer, 2005; Freeman, Borgatti, & White, 1991; Newman, 2005). In addition, Opsahl and colleagues (2010) proposed generalizations of degree, closeness, and betweenness centralities by combining in the formula both the number and the weights of the edges. They introduced a tuning parameter that allows setting their relative importance: a higher value of the tuning parameter emphasizes the importance of the weights over the mere presence of the ties and vice versa. Another important family of centrality indices defines the centrality of a node as recursively dependent on the centralities of their neighbors. Among the most prominent of those indices are *eigenvector centrality* (Bonacich, 1972, 2007), Bonacich power (Bonacich, 1987) and *alpha centrality* (Bonacich & Lloyd, 2001).

Clustering Coefficients

Besides centrality, other network properties have been investigated that are relevant also for personality networks. The local *clustering coefficient* is a node property defined as the number of connections among the neighbors of a focal node over the maximum possible number of such connections (Watts & Strogatz, 1998). If we define a triangle as a triple of nodes all connected to each other, the clustering coefficient can be equally defined as the number of triangles to which the focal node belongs, normalized by the maximum possible number of such triangles. The clustering coefficient is high for a node i if most of i's neighbors are also connected to each other and it is important to assess the small-world property (Watts & Strogatz, 1998; Humphries & Gurney, 2008), as we detail below. Consider for instance the node D in Figure 10.1, which has three neighbors, A C, and E. Of the three possible connections among its neighbors, only one is present (the one between A and E), therefore its clustering coefficient is 1/3.

The clustering coefficient can be also interpreted as a measure of how much a node is redundant (Latora, Nicosia, & Panzarasa, 2013; Newman, 2010): if most of a node's neighbors are also connected with each other, removing that node will not make it harder for its neighbors to reach or influence each other. A personality characteristic that has a high clustering coefficient is mainly connected to other personality features that are directly related to each other. In personality questionnaires the strongest connections are usually among nodes of the same subscale: in these cases, having a high clustering coefficient may coincide with having most connections with other nodes belonging to the same subscale, while having no large connection with nodes of other scales.

While in its original formulation the clustering coefficient can be applied only to unweighted networks (or to weighted networks, disregarding the information about weights), it has been recently generalized to consider positive edge weights (Saramäki, Kivelä, Onnela, Kaski, & Kertesz, 2007). The first of such generalizations was proposed by Barrat and colleagues (2004) and has been already discussed in the context of personality psychology and psychopathology (Borsboom & Cramer, 2013). Onnela and colleagues (2005) proposed a generalization that is based on the geometric averages of edge weights of each triangle centered on the focal node. A different generalization has been proposed in the context of gene co-expression network analysis by Zhang and Horvath, which is particularly suited for networks based on correlations (Kalna & Higham, 2007; Zhang, Horvath, et al., 2005). All of these generalizations coincide with the unweighted clustering coefficient when edge weights become binary (Saramäki et al., 2007). Recently three formulations of clustering, the unweighted clustering coefficient (Watts & Strogatz, 1998), the index proposed by Onnela et al. (2005) and the one proposed by Zhang et al. (2005) have been generalized to signed networks and the properties of such indices have been discussed in the context of personality networks (Costantini & Perugini, 2014).

Transitivity (or global clustering coefficient) is a concept closely connected to clustering coefficient that considers the tendency for two nodes that share a neighbor to be connected themselves for the entire network, instead than for the neighborhood of each node separately. It is defined as three times the number of triangles, over the number of connected triples in the network, where a connected triple is a node with two edges that connect it to an unordered pair of other nodes (Newman, 2003). Differently from the local clustering coefficient, transitivity is a property of the network and not of the single nodes. For instance, the network in Figure 10.1 has one triangle (A, D, E) and 12 connected triples, therefore its transitivity is $3 \times 1)/12 = 1/4$. Transitivity has been extended by Opsahl and Panzarasa (2009) to take into account edge weights and directions, and by Kunegis and collaborators to signed networks (Kunegis et al., 2009).

Small Worlds

The transitivity and clustering coefficient can be used to assess the network *small-world property*. The small-world property was initially observed in social networks as the tendency for any two people to be connected by a very short chain of acquaintances (Milgram, 1967). The small-world property is formally defined as the tendency of a network to have both a high clustering coefficient and a short average path length (Watts & Strogatz, 1998). Small-world networks are therefore characterized by both the presence of dense local connections among the nodes and of links that connect portions of the network otherwise far away from each other. An index of *small-worldness* for unweighted and undirected networks has been proposed as the ratio of transitivity to the average distance between two nodes. Both transitivity and path length are standardized before the computation of small-worldness, by comparing them to the corresponding values obtained in equivalent random networks (with the same N and the same degree distribution). Alternatively, the index can be computed using the average of local clustering coefficients instead of transitivity. A network with a small-worldness value higher than three can be considered as having the small-world property, while a small-worldness between one and three is considered a borderline value (Humphries & Gurney, 2008). Because the assessment of small-worldness relies on shortest paths between all the pairs of nodes, it can be computed only for a connected network or the giant component of a disconnected network.

Application to the HEXACO Data

Centrality analyses. The function `centrality_auto` allows to quickly compute several centrality indices. It requires the weights matrix as input. The function automatically detects the type of network and can handle both unweighted and weighted networks, and both directed and undirected networks. For a weighted and undirected network, the function gives as output the node strength, the weighted betweenness and the weighted closeness centralities. The edge betweenness centrality is also computed.

```
centrality <- centrality_auto(network)
nc <- centrality$node.centrality
ebc <- centrality$edge.betweenness.centrality
```

The centrality values are computed and stored in variable `centrality`. Node centralities are then saved in the variable `nc` while edge betweenness centralities are saved in the variable `ebc`. The values of centrality for each node are reported in Table 10.2. The command `centralityPlot(network)` can be used to plot the centrality indices in a convenient way, that allows to quickly compare them. Table 10.3 reports the correlations among the three indices of node centrality together with Hofmann's (1978) row-complexity and the squared multiple correlation of each facet with all the others. All the indices of centrality have positive significant correlations with each other. Strength centrality and, to a lower extent, betweenness centrality, seem to be favored by row-complexity: sharing variance with more than one factor allows a facet to play a more central role. These results suggest that, in this network, facets tend to be central to the whole network and not only to their purported parent traits. All centrality indices, especially strength and closeness, correlate with the squared multiple correlations: The more variance a facet shares with other facets, the stronger are its connections and the more central results the corresponding node[6].

[6] Despite being substantial, the correlations of centrality indices with row-complexity and squared multiple correlations do not suggest that the indices fully overlap. Moreover, the relations can vary substantially and it is possible to imagine situations in which the relations are absent or even in the opposite direction.

Node	Dimension Facet	Betweenness	Closeness	Strength	
Hsi	Honesty-Humility	Sincerity	5	2.66	0.73
Hfa	Honesty-Humility	Fairness	**31**	3.03	**1.46**
Hga	Honesty-Humility	Greed-avoidance	14	2.83	1.13
Hmo	Honesty-Humility	Modesty	0	2.14	0.45
Efe	Emotionality	Fearfulness	6	2.70	1.03
Ean	Emotionality	Anxiety	2	3.04	1.10
Ede	Emotionality	Dependence	3	3.02	1.05
Ese	Emotionality	Sentimentality	17	3.17	**1.40**
Xss	Extraversion	Social self-esteem	11	3.11	**1.35**
Xsb	Extraversion	Social boldness	**23**	**3.33**	1.21
Xso	Extraversion	Sociability	7	**3.19**	1.07
Xli	Extraversion	Liveliness	12	3.12	1.29
Afo	Agreeableness vs. anger	Forgiveness	5	2.70	1.00
Age	Agreeableness vs. anger	Gentleness	5	2.66	0.80
Afl	Agreeableness vs. anger	Flexibility	14	2.90	1.02
Apa	Agreeableness vs. anger	Patience	5	2.85	0.85
Cor	Conscientiousness	Organization	7	3.09	0.99
Cdi	Conscientiousness	Diligence	**26**	**3.34**	1.30
Cpe	Conscientiousness	Perfectionism	5	3.13	1.26
Cpr	Conscientiousness	Prudence	**19**	**3.52**	**1.45**
Oaa	Openness to experience	Aesthetic appreciation	14	2.95	1.24
Oin	Openness to experience	Inquisitiveness	5	2.71	1.08
Ocr	Openness to experience	Creativity	10	3.00	1.26
Oun	Openness to experience	Unconventionality	3	2.63	0.98

Table 10.2: Centrality Indices. Note: the four most central nodes according to each index are reported in bold.

	1	2	3	4	5
1. Betweenness	1	.61**	.72***	.32	.54**
2. Closeness	.61**	1	.75***	.15	.69***
3. Strength	.70***	.82***	1	.47*	.75***
4. Complexity	.41*	.28	.43*	1	.11
5. SMC	.56**	.73***	.79***	.12	1

Table 10.3: Correlation of node centralities, row-complexity and squared multiple correlation (SMC). Note: $* = p < .05$, $** = p < .01$, $*** = p < .001$. Pearson correlations are reported below the diagonal, Spearman correlations are reported above the diagonal. Complexity = Hofmann's row-complexity index. SMC = squared multiple correlation.

The three indices of centrality converge in indicating that node Cpr (prudence) is among the four most central nodes in this network. Cpr is also the more closeness central node and owes its high centrality to the very short paths that connect it to other traits. For instance, facets Apa (patience), Xso (sociability), and Xss (social self-esteem) are even closer to Cpr than other conscientiousness facets are[7]. This suggests that in the personality network it is very easy that a change in some portion of the network will eventually make a person either more reckless or more prudent. On the other hand, if a person becomes more reckless or more prudent, we can expect important changes in the overall network. This result, although it should be considered as preliminary, is in line with studies that investigated the evolution of conscientiousness. Impulse-control, a facet of conscientiousness that is very similar to prudence (Cpr), shows the most marked variation through the individual development compared to other conscientiousness facets (Jackson et al., 2009). It is possible that this is the case also because changes in other personality traits are expected to affect prudence more quickly than other facets, as revealed by its high closeness.

Hfa (fairness) is the most betweenness-central and strength-central node, but it is not particularly closeness-central (it is ranked 10th in closeness centrality). Figure 10.3 highlights the edges lying on the shortest paths that travel through node Hfa, in a convenient layout (the code for producing this figure is in the supplemental materials). The high betweenness centrality of Hfa is due the role that Hfa plays in transmitting the influence of other honesty-humility facets to different traits, and vice versa. The edge between nodes Hsi (sincerity) and Hfa is also the most betweenness-central in the whole network: most of the shortest paths between Hsi and other personality traits travel through this edge and therefore through Hfa. These results suggest that, if it was possible to reduce the possibility for fairness (Hfa) to vary, the influence of the other honesty-humility facets would propagate less easily to the rest of personality facets and vice versa. Such hypotheses could be tested for instance by comparing the personality networks of individuals that typically face situations in which their fairness is allowed to become active to the networks of individuals that usually face situations in which their fairness cannot be activated (Tett & Guterman, 2000). The characteristics of situations for instance could be assessed by using valid instruments such as the Riverside Situational Q-sort (Sherman, Nave, & Funder, 2010), which includes items such as “It is possible for P to deceive someone”, or “Situation raises moral

[7] As an anonymous reviewer pointed out, one could wonder how can the length of the path between Cpr and other conscientiousness facets be longer than the path between Cpr and other nodes, given that Cpr’s strongest correlations are those with the other conscientiousness facets. This happens because we did not consider the network defined by the zero-order correlations, but the adaptive LASSO penalized network of partial correlations (Krämer et al., 2009). As an example, consider the shortest path between Cpr and Cdi (diligence), which is slightly longer (8.80) than the shortest path between Cpr and Apa (patience; 6.82). Although the correlation between Cpr and Cdi is stronger ($r = .26$) than the correlation between Cpr and Apa ($r = .22$), in the adaptive LASSO network, the direct connection between Cpr and Cdi is smaller ($pr = .04$) than the one with Apa ($pr = .15$). While the shortest path between Cpr and Apa travels through their direct connection, the shortest path between Cpr and Cdi travels through node Cor (organization): prudence seems to influence (or to be influenced by) diligence especially through changes in orderliness, but this path of influence is longer than the direct path between Cpr and Apa.

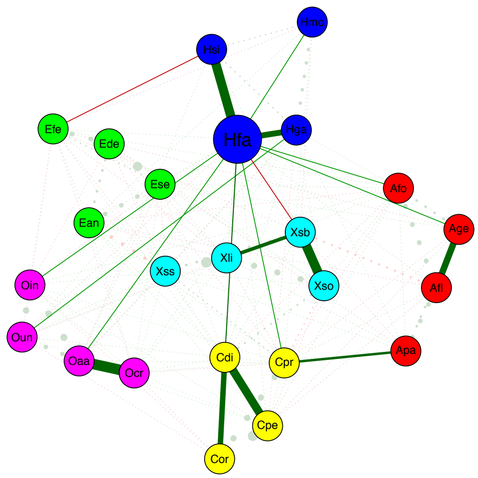

Figure 10.3: Shortest paths that pass through node Hfa (fairness). The edges belonging to the shortest-paths are full, while the other edges are dashed.

or ethical issues" that would be relevant for this case.

Clustering coefficients. Many indices of clustering coefficient can be easily computed using function `clustcoef_auto`. The function requires the same input as `centrality_auto` and is similarly programmed to recognize the kind of data given as input and to choose an appropriate network representation for the data. By applying the function, we can immediately collect the results:

```
clustcoef <- clustcoef_auto(network)
```

The command `clusteringPlot(network, signed = TRUE)` can be used to plot the clustering coefficients in a convenient layout. Table 10.4 reports the correlation among several clustering coefficients. The unsigned indices are computed using the absolute values of the weights. In the following analyses we will use the signed version of the Zhang's clustering coefficient (Costantini & Perugini, 2014; Zhang et al., 2005), which resulted more resistant to random variations in the network.

Combining clustering coefficients and centrality. The signed clustering coefficient can be interpreted as an index of a node's redundancy in a node's neighborhood (Costantini & Perugini, 2014): the importance of the unique causal role of highly clustered nodes is strongly reduced by the presence of strong connections among their neighbors. In general, it is interesting to inspect whether there is a relation between centrality indices and clustering coefficients: in our experience, we found that the centrality indices were often inflated by the high

	1	2	3	4	5	6	7
1. Watts and Strogatz (1998)	1	.25	.65***	.51*	.90***	.57**	.94***
2. Watts and Strogatz, signed (Costantini & Perugini, 2014)	.26	1	.28	.45*	.29	.76***	.25
3. Zhang and Horvath (2005)	.49*	.30	1	.89***	.50*	.59**	.71***
4. Zhang and Horvath, signed (Costantini & Perugini, 2014)	.34	.33	.94***	1	.37	.79***	.53**
5. Onnela et al. (2005)	.89***	.25	.37	.24	1	.55**	.84***
6. Onnela et al., signed (Costantini & Perugini, 2014)	.61**	.76**	.59**	.64**	.66***	1	.53**
7. Barrat et al. (2004)	.94***	.30	.57**	.37	.87***	.60**	1

Table 10.4: Correlation among indices of local clustering coefficient. Note: $* = p < .05$, $** = p < .01$, $*** = p < .001$. Pearson correlations are reported below the diagonal, Spearman correlations are reported above the diagonal.

clustering in correlation networks. However this might be not true for networks defined with adaptive LASSO, which promotes sparsity (Krämer et al., 2009).

The following plots can be used to visualize both the centrality and the clustering coefficient of each node. The code reported here is for betweenness centrality, but it is easy to extend it to other indices by just replacing `"Betweenness"` with the index of interest. First the plot is created and then the node labels are added in the right positions, using the command text. Command `abline` can be used to trace lines in the plot. A horizontal line is created to visually identify the median value of betweenness and a vertical line to identify the median value of the clustering coefficient.

```
plot(clustcoef$signed_clustZhang, nc$Betweenness,
     col = "white")
text(clustcoef$signed_clustZhang, nc$Betweenness,
     rownames(nc))
abline(h = median(nc$Betweenness), col = "grey")
abline(v = median(clustcoef$signed_clustZhang),
     col = "grey")
```

The resulting plots are shown in Figure 10.4. It is apparent that the most central nodes do not have a particularly high clustering coefficient in this case and this is especially true for nodes Hfa and Cpr, which are among the most central in this network. The clustering coefficient correlates negatively with closeness centrality ($r = -.67$, $p < .001$), with strength ($r = -.82$, $p < .001$), and with betweenness centrality ($r = -.50$, $p = .013$).

One node, Hmo (modesty), emerges as both particularly high in clustering coefficient and low in all the centrality measures. Modesty correlates almost exclusively with other honesty-humility facets and has the lowest multiple correlation with all the other variables in our dataset and this is likely to have determined its peripherality. A closer exam of its connections reveals that Hmo has seven neighbors, the three other facets of honesty-humility (His, Hfa, and Hga), facets anxiety and fearfulness of emotionality (Ean), facet social boldness of extraversion (Xsb) and facet prudence of conscientiousness (Cpr), the connections with fearfulness, social boldness and prudence having very small weights. Moreover many of its neighbors are connected with each other. Even if the edges incident in node Hmo were blocked, its neighbors would be nonetheless connected to each other directly or by a short path. Modesty therefore does not seem to play a very important unique role in the overall personality network.

Transitivity and small-worldness. The function `smallworldness` computes the small-worldness index (Humphries & Gurney, 2008). First the function converts the network to an unweighted one, which considers only the presence or the absence of an edge. Then the average path length and the global transitivity of the network are computed and the same indices are calculated on B=1000 random networks, with the same degree distribution of the focal network. The resulting values are entered in the computation of the small-worldness index. The output includes the small-worldness index, the transitivity of the network, and its average path length. It also returns summaries of the same indices computed on the random networks: the mean value and the .005 and .995 quantiles of the distribution. Function `set.seed` can be used to ensure the exact replicability of the results. The function requires the network as input and it is optionally possible to set the values of three parameters, `B`, `up` and `lo`, which are respectively the number of random networks and the upper and lower probabilities for the computation of the quantiles.

```
set.seed(100)
smallworldness(network)
```

The small-worldness value for our network is 1.01. An inspection of the values of transitivity and of average path length shows that they are not significantly different from those emerged from similar random networks. Therefore we may conclude that this personality network does not show a clear small-world topology.

Emerging insights. In this section, we showed how it is possible to perform a network analysis on a real personality dataset. We identified the most central nodes and edges, discussed centrality in the light of clustering coefficient and investigated some basic topological properties of the network, such as the small-world property. Two nodes resulted particularly central in the network and were the facet prudence of conscientiousness (Cpr) and the facet fairness of honesty-humility (Hfa).

Our network did not show the small-world property. The absence of a strong transitivity means that the connection of two nodes with a common neighbor does not increase the probability of a connection between themselves. The absence of a particularly short path length implies that it is not generally possible for any node to influence any other node using a short path. This result is not in line with the small-worldness property that emerged in the DSM-IV network reported by

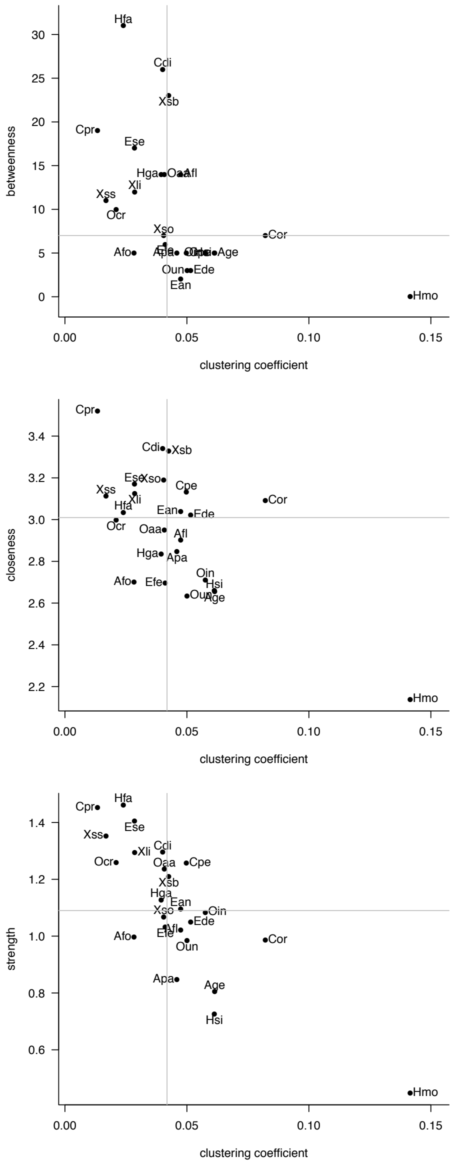

Figure 10.4: Centrality and clustering coefficient. The horizontal and the vertical lines represent the median values of centrality and clustering coefficient respectively. The closeness values are multiplied by 1000.

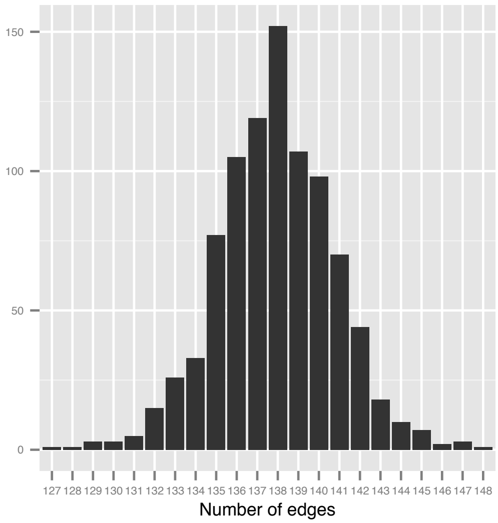

Figure 10.5: Histogram of the number of edges estimated in 900 replications of the adaptive LASSO.

Borsboom et al. (2011). It has been hypothesized that the small-world property might be at the basis of phenomena connected to the comorbidity that arise in psychopathology (Cramer et al., 2010); this also may simply not be a property of normal personality. This difference could reflect the fact that different personality characteristics represent distinct systems, while psychopathology systems seem to be more integrated. This result may be also attributable to the strategies that were used for defining this network and the DSM-IV network and may have been influenced by the particular personality scales under study. Future research may be directed towards the question of what network structure characterizes normal versus abnormal personality.

Stability of Results

The adaptive LASSO chooses the LASSO penalty parameter based on k-fold cross-validation, subdividing the dataset in k (10 by default) random samples. Because of this, under different random seeds slightly different network structures will be obtained. To investigate the stability of the results discussed in this section, we repeated the network estimation procedure 900 times under different random seeds and recomputed the strength, closeness and betweenness centrality measures and the signed versions of the clustering coefficients proposed by Zhang and by Onnela. The codes to replicate these findings can be found in the supplementary materials.

Visually the resulting graphs looked remarkably similar and only differed in the weakest edges in the graph. Figure 10.5 shows a histogram of the amount of nonzero connections present in each of the replications; the median amount of

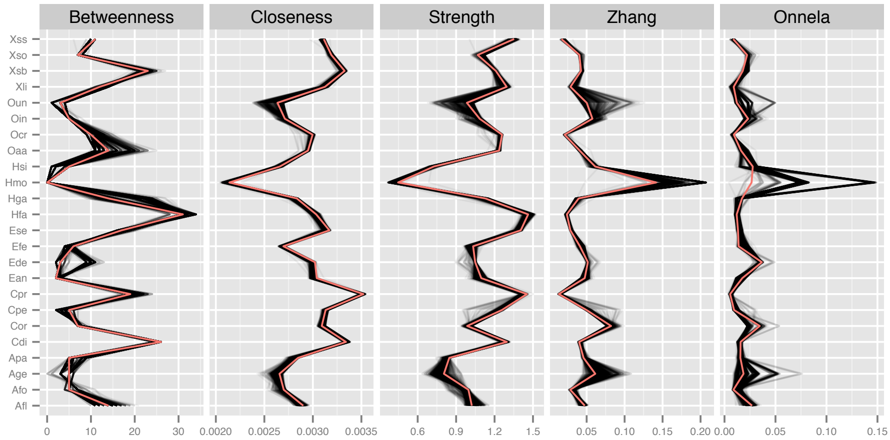

Figure 10.6: Estimated centrality and clustering coefficients under 900 replications of the adaptive LASSO. The colored line represents the results discussed in the chapter.

estimated edges was 138. Figure 10.6 shows the estimated centrality and clustering coefficients for both the graph used in the analyses (colored line) and the 900 replications (vague gray lines). It can be seen that overall the measures are stable across different replications. Among the three centrality measures, more stable results were obtained for closeness and strength than for betweenness. Between the clustering coefficients we can see that Zhang's clustering coefficient is much more stable than Onnela's; in Onnela's clustering coefficient especially the Hmo node shows divergent behavior. This behavior is due to the number small of connections of Hmo obtained in each replication, ranging from 3 to 11 (M = 3.96, SD = 0.64). Onnela's clustering coefficient is scaled to the number of connections regardless of weight. Therefore the relatively small difference in connections can have a large impact on this clustering coefficient.

From these results, we advise that Zhang's clustering coefficient should be preferred over Onnela's clustering coefficient in adaptive LASSO networks. Furthermore, we advise the reader to replicate these measures under different random seeds and to check for the stability of the results before substantively interpreting them.

10.4 Conclusion

Network approaches offer a rich trove of novel insights into the organization, emergence, and dynamics of personality. By integrating theoretical considerations (Cramer et al., 2010), simulation models (Mõttus, Penke, Murray, Booth, & Allerhand, 2014; Van Der Maas et al., 2006), and flexible yet user-friendly data-analytic techniques (Epskamp et al., 2012), network approaches have potential to achieve a tighter fit between theory and data analysis than has previously been achieved in personality research. At the present time, the basic machinery for generating, analyzing, and simulating networks is in place. Importantly, the R platform offers an impressive array of packages and techniques for the researcher to combine, and most of the important analyses are currently implemented. We hope that, in the present chapter, we have successfully communicated the most important concepts and strategies that characterize the approach, and have done so in such a way that personality researchers may benefit from using network modeling in the analysis of their own theories and datasets.

In the present chapter, we have applied network modeling to an illustrative dataset, with several intriguing results that may warrant further investigation. However, we do stress that many of our results are preliminary in nature. The primary reason for this is that current personality questionnaires are built according to psychometric methodology that is tightly coupled to factor analysis and classical test theory (Borsboom, 2005). This makes their behavior predictable from pure design specifications, which in turn limits their evidential value. That is, if one makes the a priori decision to have, say, 10 items per subscale, and selects items on the basis of their conformity to such a structure, many of the correlations found in subsequent research are simply built into the questionnaire. Therefore, it is hardly possible to tell to what extent results reflect a genuine structure, or are an artifact of the way personality tests are constructed. Trait perspectives are not immune to this problem, as in some cases the factors of personality may simply appear from questionnaire data because they have been carefully placed there. Future research should investigate potential solutions to this issue, for instance by considering variable sets consisting of ratings on the familiar personality-descriptive adjectives of a language, as in lexical studies (e.g., Ashton & Lee, 2005, 2007; De Raad et al., 2014; Goldberg, 1990b; Saucier et al., 2014), and by comparing the characteristics of such networks to networks that emerge from questionnaire data.

An interesting question is whether all individuals are scalable on all items, as current methodology presumes. It is entirely possible, if not overwhelmingly likely, that certain items assess variables that simply do not apply to a given individual. Current psychometric methods have never come to grip with the "n.a." answer category, and in practice researchers simply force all individuals to answer all items. In networks, it is easier to deal with the n.a.-phenomenon, as nodes deemed to be inapplicable to a given person could simply be omitted from that person's network. This would yield personality networks that may differ in both structure and in size across individuals, an idea that resonates well with the notion that different people's personalities might in fact be also understood in terms of distinct theoretical structures (Borsboom et al., 2003; Cervone, 2005; Lykken, 1991). The application of experience sampling methodology and of other ways to gather information on dynamical processes personality may also offer an inroad into this issue (Fleeson, 2001; Hamaker, Dolan, & Molenaar, 2005; Bringmann et al., 2013).

The notion that network structures may differ over individuals, and that these differences may in fact be the key for understanding both idiosyncrasies and communalities in behavior, was illustrated in the simulation work reported by

Costantini and Perugini (2014). Future research might be profitably oriented to questions such as (a) what kind of structural differences in networks could be expected based on substantive theory, (b) how such differences relate to well-established findings in personality research (see also Mõttus et al., 2014), (c) which network growth processes are theoretically supported by developmental perspectives. Of course, ultimately, such theoretical models would have to be related back to empirical data of the kind discussed in the data-analysis part of this chapter; therefore, a final highly important question is to derive testable implications from such perspectives. This includes the investigation of how we can experimentally or quasi-experimentally distinguish between explanations based on latent variables, and explanations based on network theory.

Ideally, these future developments are coupled with parallel developments in statistical and technical respects. Several important extensions of network models are called for. First, in this work we focused on the adaptive lasso, which is an effective method to extract a network from empirical data that has been profitably used in other fields (Krämer et al., 2009). However network analysis is a field in rapid evolution and alternative methods are being developed and studied. Among these, we consider particularly promising the graphical lasso (Friedman et al., 2008), for which adaptations exist that take into account the presence of latent variables in the network (Chandrasekaran et al., 2012; Yuan, 2012). Alternative methods based on Bayesian approaches have also been proposed and implemented (Mohammadi, Wit, et al., 2015). Further research is needed to systematically compare these and other methods in the complex scenarios that are usually encountered in personality psychology. Second, as noted in this chapter, many network analytics were originally designed for unweighted networks. Although some of the relevant analyses have now been extended to the weighted case (see Boccaletti et al., 2006; Opsahl et al., 2010; Costantini & Perugini, 2014, several other techniques still await such generalization. One important such set of techniques, which were also illustrated in the present work, deals with the determination of network structure. Both the theoretical definition of global structures, such as in terms of small-worlds, scale-free networks (Barabási, 2009), and random networks, and the practical determination of these structures (e.g., through coefficients such as small-worldness or through fitting functions on the degree distribution) are based on unweighted networks. It would be highly useful if these notions, and the accompanying techniques, would be extended to the weighted network case. Another technical improvement that should be within reach is how to deal with data that likely reflect mixtures of distinct networks. In the case of time series data, such approaches have already been formulated through the application of mixture modeling (Bringmann et al., 2013); however, statistical techniques suited to this problem may also be developed for the case of cross-sectional data. The issue is important in terms of modeling idiosyncrasies in behavior, but may also be key in terms of relating normal personality to psychopathology (Cramer et al., 2010). Naturally, this includes the question of how we should think about the relation between normal personality and personality disorders.