

# Towards a Structural Typology of Personal Networks

*Keywords: social network analysis, structural typology, personal networks, friendship, clustering*

## Extended Abstract

Personal (egocentric) network research delves into the social relations of individuals. Briefly, the personal network (PN) of an individual (from now on ‘ego’) is the network composed by all the people around ego with whom ego has a personal relationship (from now on ‘alteri’) and the relations between them. In other words, in the PN of ego, nodes represent alteri and edges represent personal relationships between alteri (e.g., friendships). Our work focuses on the identification of the basic dimensions influencing the structural variability of PNs, and on the possibility of developing a structural typology for them. This research line serves to different purposes. Aside from the basic proposition that personal network patterns, beyond the level of dyads, deeply affect ego’s life [1], understanding the basic underlying structure may help us discover which network attributes are related to each other and which of them are necessary to characterize and distinguish PNs. This knowledge would allow to make direct comparisons of PNs across time and societies [2]. More importantly, a robust typology can uncover some of the underlying ‘rules’ (e. g., ecological constraints, cultural features, or personality traits) that influence the individual’s network construction process and make some configurations of personal networks more likely than others. In this paper, we provide such a typology by means of an agnostic clustering process that sheds light on previously proposed classifications based on purely qualitative interpretations, leading to a more solid ground for this theoretical approach.

We study a dataset containing 362 PNs from students in a high school, where all the alteri belong to the same school. In order to uncover the structural typology of these PNs, we first select the structural features of the network we will use to characterize them, namely, network size, network density, number of components and isolated nodes, betweenness centralization, median closeness, and density of triangles. These variables are chosen using similar criteria than previous works in order to be able to compare results [3, 4]. Subsequently, we apply a series of outlier detection algorithms (isolation forests, local outlier factor and one-class support vector machine) to clean the dataset. Finally, we apply different classification algorithms (*k-means*, *gaussian mixture* and *bayesian gaussian mixture*) to construct inductively a typology of PNs. To validate our findings, we compare our results with two different null models: one to validate the algorithm’s functioning and the other to establish a baseline with which to assess whether we could have obtained our results by chance.

We find a robust classification of personal networks in 6 types according to the seven structural variables (see Fig. 1):

- *DENSE* type: small networks with high density, closeness and number of triangles, moderately low number of components, isolated nodes and betweenness centralization. These networks usually consist of a single component in which all the alteri are densely connected among them.
- *CENTERED* type: small networks with high betweenness centralization, with notably high closeness, density and number of triangles, and low number of nodes, components

and isolated nodes. These networks are characterized by the presence of different subgroups in which all the alteri are connected among them within the group, and different groups are connected by a highly central node.

- *DISSOCIATED* type: large networks with high number of components, nodes and isolated nodes, intermediate betweenness centralization and low closeness, density and number of triangles. These networks tend to be formed by several groups or isolated nodes that are not connected between them.
- *COMPOSITE* types I and II: intermediates values in all variables, the difference between type I and type II networks being that the latter tend to be smaller with a lower number of components.
- *SPARSE* type: small networks with very low values in density, median closeness, betweenness centralization and number of triangles and intermediate values of components and isolated nodes.

While our structural typology is compatible with previous results [3, 4], our work is an important advance in the field in two directions. First, those previous studies argue that different types of PNs appear due to differences in the contexts of interaction of each person (family, hobbies, work, etc.). However, we find compatible types in a single context of interaction: the high school. Thus, our results suggest that typologies may be caused by other conditions (like personality traits or cultural roles/expectations). Second, these analyses relied on some steps in which they had to make arbitrary choices, for instance, constructing the typology empirically by means of visually analyzing individual networks or selecting manually the number of types beforehand. Our assessment finds automatically the optimal number of clusters and develops a differentiated typology that is interpreted sociologically afterwards. Our approach will allow us to unveil the basic dimensions of structural variability of PNs in order to avoid selecting arbitrarily the variables to use. Eliminating this part of the process will provide a *general* structural typology of PNs that could be validated across different datasets, thus establishing its universality and also its context-dependence nuances.

## References

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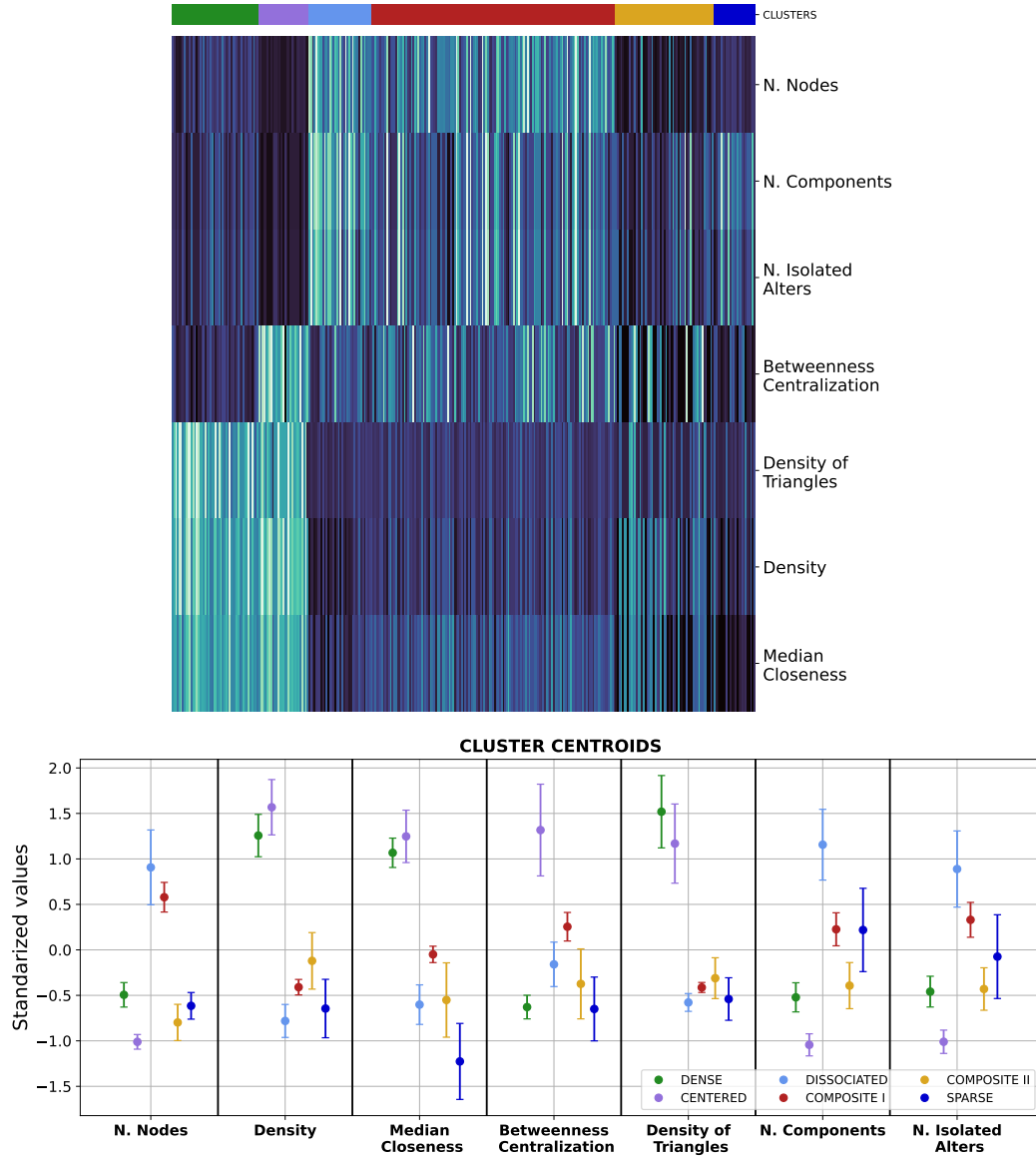


Figure 1: **TOP:** A so-called ‘clustermap’, where each column represents a network sample, each row represents a structural feature of the network and colors represent the standardized intensity of each feature (the lighter the color, the higher the standardized value). Samples (columns) are ordered by cluster, such that they share common features with other samples next to them. In this way, it is direct to inspect visually the microscopic behavior of structural features within clusters. **BOTTOM:** Mean of each structural variable for each type of network, where the error bars represent the bounds of the 95% confidence interval for the estimation of the means.