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## Recognizing modes of acculturation in personal networks of migrants<sup>☆</sup>

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### Abstract

An individual's personal network encodes social contacts as well as relations among them. Personal networks are therefore considered to be characteristic and meaningful variables of individuals—supplementing more traditional characteristics such as age, gender, race, or job position.

We analyze an ensemble of several hundred personal networks of migrants using a recently introduced classification method. As a result, individuals are partitioned into groups defined by similarity of their personal networks, and abstract summaries of classes are obtained. From the analysis we can conclude that Berry's modes of acculturation feature prominently in the empirical data.

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**Keywords:** Personal networks, network ensemble, role structure, acculturation

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### 1. Introduction

In social science individuals are often characterized and distinguished by personal attributes such as age, gender, race, job position, or income. Additional meaningful information is given by an individual's personal network, i. e., his or her social contacts and the relations among them (McCarty, 2002). For instance, personal networks have been used to address the community question (Wellman, 1979), and their structure has been associated with psychological indicators (Kalish and Robins, 2006). Moreover, personal networks have been used to define user roles in Usenet newsgroups (Welser et al., 2007) and to characterize the acculturation of migrants (Brandes et al., 2008; Molina et al., 2008).

Note that personal network analysis is usually concerned with a *set* of networks rather than a single instance (see, e. g., Faust and Skvoretz 2002; Butts and Carley 2005; Faust 2006). In this paper we refer to a set of networks that stem from a common underlying process such as repeated data collection by using the same questionnaire as a *network ensemble* (Brandes et al., 2009).

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property, such as density, clustering coefficient, or degree distributions. In this paper comparisons are based on two aspects: (1) “who is in the network”, i. e., what are the individual characteristics of the *alters* in a network and (2) “how are they connected”, i. e., what is the structure of ties among the alters. We group networks that are similar in these respects and thereby analyze the ensemble for patterns of typical social environments.

Specifically, we study personal network of migrants (Brandes et al., 2008; Molina et al., 2008) by adapting a recently introduced method for classification in network ensembles based on latent roles (Brandes et al., 2010). This approach is unique in the study of personal networks as it combines network composition and structure in a single measure, rather than analyzing these variables separately. After introducing the data set in Section 2, we briefly outline the method and discuss its adaptation to the current study in Section 3. Results are discussed in Section 4 and we conclude in Section 5.

## 2. Empirical Data

In the following we describe the data set that is the object of our analysis. It consists of a number of personal networks collected from interviews with 504 immigrants to Spain and the USA using the EgoNet<sup>1</sup> software. Each network describes the social environment of a migrant originating from a South-American, Middle-American, African, or East-European country. The data was already described in Brandes et al. (2008), but we reproduce the main aspects for convenience.

Each respondent was asked to provide the following four types of information:

1. **(questions about ego)** 70 questions about the respondent herself, including age, skin color, years of residence, questions from traditional acculturation scales and health related questions
2. **(name generator)** A list of 45 persons (referred to as *alters*) personally known to the respondent. The alters are the nodes in the respondent’s personal network.
3. **(questions about alters)** 12 questions about each of the 45 alters, including country of origin, country of residence, skin color, and type of relation to ego.
4. **(ties between alters)** For each of the 990 undirected pairs of alters, ego specified “What is the likelihood that Alter1 and Alter2 have a relationship independent of you?” by choosing “very likely,” “maybe,” or “unlikely.” The relations have been binarized with “very likely” as the threshold.

While the data on each individual is rich already, the full data set is even more complex. From a purely statistical point of view, each migrant is described by a feature vector with several hundred entries. In the present analysis we concentrate on the structure of personal networks and consider as attributes only the countries of origin and residence of the alters compared with those of ego. In other words, we distinguish alters only with respect to their immigration situation relative to ego.

Our modeling of roles and connections between roles relates to the framework for social interaction described in Nadel (1957). In this framework, roles are strongly connected to attributes of persons enacting them. It is further postulated that there is a strong association between roles and both qualitative and quantitative aspects of relationships within society. Compared to the more fine-grained role structure presumed by Nadel, we here employ a rather simplistic and abstract view of roles and relationships. In our analysis we concentrate on high-level aspects of acculturation, so that roles are determined completely by a small subset of known attributes describing alters relative to ego. This leads to a very small set of stylized roles that apply to the entire ensemble, and thus enable a quantitative comparison of its members.

Our driving proposition is that alter roles are defined by individual attributes, but that their structural consequences are moderated by traits of ego. In other words, alters enacting the same role in the personal networks of distinct egos may be forming alternative relational patterns, and thus reflect back on characteristics of the reporting egos.

With this proposition in mind, the composition and structure of personal networks will be related to the modes of acculturation proposed in Berry (1997). Variance in the relation between roles and interaction patterns can then be interpreted as differences in the immigration situation of the corresponding egos.

In the derivation of roles from attributes we follow the approach of Brandes et al. (2008) and distinguish alters by their countries of origin and residence, both relative ego’s. In the first step the alters of all networks are thus partitioned into four classes:

<sup>1</sup>See <http://www.egoredes.net/> for a description of the project and <http://sourceforge.net/projects/egonet/> for a description of the software.

- **fellows** - the alter stems from the same country as the ego and also immigrated
- **host** - the alter lives in the country the ego immigrated to and stems from that country
- **transnationals** - all other.

In the following we will use these assignments of the nodes to classes for the derivation of a structural description of the complete ensemble. When compared to the results of Brandes et al. (2008) for individual networks, the outcome of this process is an averaged structural description over all networks in the ensemble.

### 3. Analysis

In the following, we show a method to abstract a collection of networks by a single structural description and use it to describe our data. We further show how to group the given networks by structural similarity and thereby give an even finer description of the ensemble showing general structural trends.

Our model has similarities to blockmodels (Doreian et al., 2005) used for the abstraction of single graphs. In blockmodels the focus of interest is the relational structure within a graph and the goal is a model that groups nodes into positions such that nodes of one position are connected to nodes in other position in some admissible form. In contrast to this, our model is based on roles characterized by attributes of nodes, and relations between these positions are described only by the number of links between members of different roles. Further our intention is not to describe the structure of a single network, but to describe variance in an ensemble of networks. To some extent our analysis therefore resembles that of White et al. (1976). Here, multiple networks on the same set of actors are subjected to a blockmodeling and the resulting block assignments of the actors are compared with each other. In contrast to this we use prescribed role assignments to relate actors of different networks to each other, and analyze the sizes of role blocks and the distribution of ties between them.

We call an abstraction as described here a *class structure*. A class structure is an attributed graph where the nodes are called *classes* since they represent (disjoint) groups of nodes. The partition of the nodes described in Sec. 2 of the alters in the ensemble is used as a basis for building a role graph. In the remainder of this chapter we give a detailed description of our model and use it to analyze the collection of personal networks .

#### 3.1. A model for simplifying structural descriptions

Consider a collection of personal networks  $(V_i, E_i), i \in \{1, \dots, N\}$  with  $V_i = \{v_1^i, \dots, v_n^i\}$ ,  $v_j^i$  being the nodes described by their category  $c(v_j^i)$  which is one of the classes described in Sec. 2. In other words  $v_j^i$  is an alter (named  $j$ ) of ego  $i$  belonging to class  $c(v_j^i)$ .  $E_i$  is the set of undirected links between the nodes of  $V_i$ , described as sets of the connected nodes, that is  $\{v_j^i, v_k^i\} \in E_i$  if and only if the alters  $j$  and  $k$  in the network of ego  $i$  know each other.

The class structure of such a collection of graphs can be described as a tuple  $(P, A)$  where  $P = \{p_1, \dots, p_4\}$  is the set of classes with each  $p_i$  representing a node category  $c(p_i)$ .  $A$  is a real, symmetric  $4 \times 4$  matrix with  $A_{i,j} \in \mathbb{R}$  describing the density of the relations between the nodes of the corresponding categories  $i$  and  $j$ .

This class structure describes an ensemble of networks in the following way: The different categories of nodes are represented by the classes and the characteristic of each class is the size of the fraction of nodes that belongs to the category. The relations between the nodes of the different categories are captured as edge probabilities in  $A$ : Let  $F \subseteq V_i$  be the set of nodes of a network  $(V_i, E_i)$  belonging to class  $p_f$  and analog is  $G \subseteq V_i$  the subset assigned to  $p_g$ . Then in the ideal case, the weight derived from the number of edges between the nodes of  $F$  and nodes of  $G$  approximates the weight given in the role graph by  $A_{f,g}$ :

$$A_{f,g} \approx \frac{e(F, G)}{\sqrt{|F||G|}},$$

where  $e(F, G) = |\{\{f, g\} \in E_i : f \in F \wedge g \in G\}|$  is the number of existing edges connecting nodes in  $F$  to nodes in  $G$ . This relation is applied analogous for the cases where  $f = g$ , that is the diagonal of  $A$  describes the connection structure within the categories. Here we follow the idea from Brandes et al. (2008) that  $A_{f,g}$  denotes the geometric mean of the expected number of neighbors in the opposite position for the nodes of the two positions. Therefore we refer to the derived edge weights as *average degree* in the remainder.

Obviously for a given ensemble of networks with said attributes the optimal structural description can be obtained by assigning all nodes to the corresponding positions,

$$P_c = \bigcup_{i=1}^N \{v \in V_i : c(v) = c\}$$

and deriving the structural description by counting the edges within the individual networks:

$$A_{i,j} = \frac{1}{\sqrt{|P_i||P_j|}} \sum_{k=1}^N |\{(a,b) \in E_k : a \in P_i \wedge b \in P_j\}|.$$

Note that in this calculation the ensemble is viewed as a single network containing all networks of the ensemble.

*A first result.* The first step of our analysis yields a description of all networks in the ensemble at once. This structural summary is visualized in Figure 1. In addition to the descriptive values of class sizes and average degree, the figure

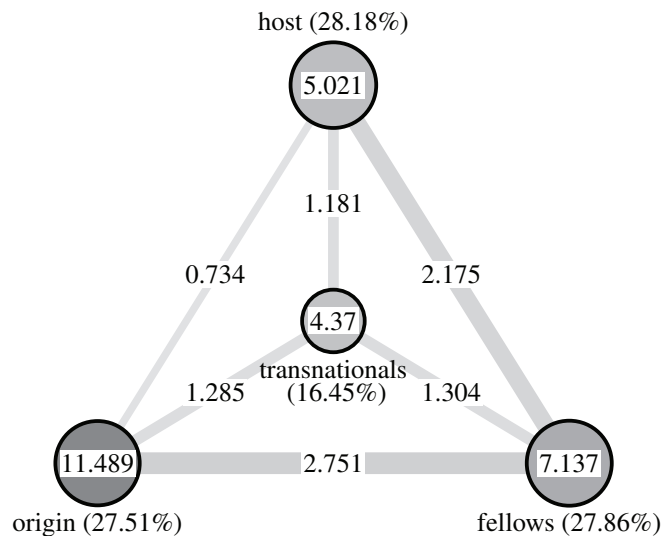


Figure 1: Class structure of the ensemble of personal networks. Node sizes express sizes of the corresponding classes, percentage of nodes in class is given in parenthesis behind the name. Edges and nodes are colored by average degree of the connections between the different classes or that of inner class connections.

gives a visual impression of the average network structure. Edges are colored according to the average degree described by them, that is the darker an edge is the higher is the average degree between nodes of the connected classes in the ensemble. Analog node colors encode the average degree within a class, while the average class size within the networks is shown as the size of the position.

This description gives an overview of the ensemble by averaging over all networks. Additional measures such as standard deviation or descriptions of outliers are missing. However, some general trends can be read from this result that seem to hold in the entire ensemble. The most obvious detail is that the individual positions seem not to differ too much in size, except for the category of transnationals. As expected the average degree of connections within the classes exceeds that between different classes and the connections between origin and fellows and between host and fellows are much stronger than all other connections between different classes. All of this could be expected from a simple geographical argumentation but with this method it can be measured and visualized.

In the following we will divide the ensemble into groups of structural similar networks and use this method of measurement and visualization to give an overview of the characteristic features of each part and thereby give an overview of the structure of the whole ensemble.

### 3.2. Network attributes from structural descriptions

From the assignment of nodes to classes we can derive an attribute vector for each network describing the matching of the network to the node classes which we will call *matching vector*. The main application of the matching vector will be to cluster the ensemble in the following steps. Given a network  $(V, E)$  we derive the components of the matching vector  $\mathbf{m} = (m_i)$  as follows: The network is viewed as an ensemble containing only this network and the class structure  $(P, A)$  is derived which is encoded in a canonical way in  $\mathbf{m}$ . The first 4 components describe the relative fraction size of each class  $c_1, \dots, c_4$  (classes enumerated in an arbitrary but fixed order):

$$m_i = \frac{|\{v_j \in V : c(v_j) = c_i\}|}{|V|}, i = 1, \dots, 4.$$

The second part of  $\mathbf{m}$  contains the average degrees. We enumerate the entries of the lower triangle of  $A$  including its diagonal:

$$m_5 = A_{1,1}, m_6 = A_{2,1}, m_7 = A_{2,2}, m_8 = A_{3,1}, \dots$$

Deriving  $\mathbf{m}$  for each network of the ensemble we obtain a description in form of an attribute vector whose size is independent of the network size. That opens the possibility to use standard clustering methods on these vectors to extract more information about the structure of the whole ensemble.

*Network distances.* The matching vector contains class sizes and average degrees given by different numbers of attributes with different scalings. For that reason, without proper normalization a fair weighting between the two characteristics cannot be guaranteed. To allow a free weighting of the individual parts we will first normalize them such that the influence of both parts on the overall distance is equal and then introduce a weighting factor  $\alpha$  that can be used to explicitly control this influence. Therefore we need the expectation of the distance of two networks described by the vectors  $\mathbf{m}_i, \mathbf{m}_j$  when only the class sizes are taken into consideration:

$$n_1 = E \left[ \|\text{diag}(1, 1, 1, 1, 0, \dots, 0)(\mathbf{m}_i - \mathbf{m}_j)\| \right],$$

and analog the expected distance for the connection part of  $\mathbf{m}$ :

$$n_2 = E \left[ \|\text{diag}(0, 0, 0, 0, 1, \dots, 1)(\mathbf{m}_i - \mathbf{m}_j)\| \right].$$

These two enable us to define a normalized,  $\alpha$ -weighted version of  $\mathbf{m}$ :

$$\mathbf{m}^\alpha = \text{diag} \left( \frac{\alpha}{n_1}, \frac{\alpha}{n_1}, \frac{\alpha}{n_1}, \frac{\alpha}{n_1}, \frac{1-\alpha}{n_2}, \dots, \frac{1-\alpha}{n_2} \right) \mathbf{m}.$$

The vector norm used for distance calculations here and throughout the rest of this paper is the  $l_1$  norm:  $\|\mathbf{a}\| = \sum_{i=1}^n |a_i|$  with  $n$  being the dimension of  $\mathbf{a}$ . Given this we can now freely adapt the focus of clustering to the class sizes, the average degrees or any combination thereof.

### 3.3. Ensemble clustering

In the next step we divide the ensemble into groups of structural similar networks. Using the result of the previous sections it is sufficient to cluster the vectors  $\{\mathbf{m}_1^\alpha, \dots, \mathbf{m}_N^\alpha\}$  describing the networks in the ensemble for some value of  $\alpha$ . The result of this clustering is a partition of the ensemble, where networks in the parts are supposed to be structural similar. Now for every part we can derive individual role graphs describing only that part of the ensemble. We can thereby give a more detailed description of the ensemble and at the same time show trends appearing in the structures of the contained networks.

*Clustering details.* For simplicity of implementation and since a detailed examination of different clustering approaches is out of scope for this paper we chose the k-means algorithm to find an appropriate clustering of the networks. We took into consideration clusterings with 2 to 20 clusters. To take care of the non-deterministic nature of the initialization of k-means we further repeated the clustering for each size 1000 times with random initialization. Experiments show that this leads to reproducible clusterings of the given data set. We compared the clusterings resulting from the different iterations and parameters with the silhouette coefficient to get an impression of how well the number of clusters fits the data. The silhouette coefficient sets inner cluster distances in contrast to distances to the nearest cluster and is to be maximized for an optimal clustering in this sense. We do not state that a clustering which maximizes the silhouette measure leads to an optimal grouping of the ensemble. It is used as a method to quantify the quality of different clusterings providing an orientation when comparing different clusterings.

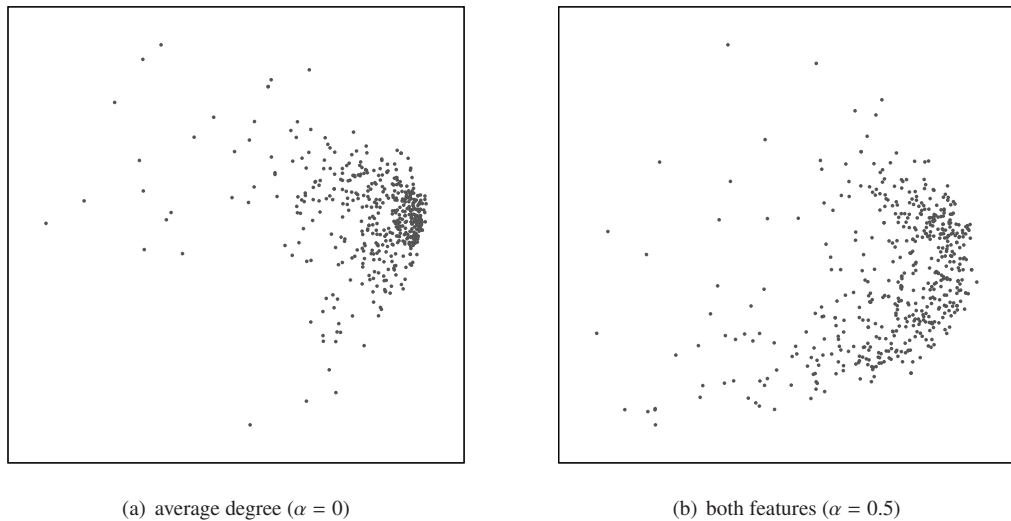


Figure 2: MDS plots of the ensemble showing spatial distributions based on network similarity derived from average degree ( $\alpha = 0$ ) and an equal mixture of the influence of average degree and class sizes ( $\alpha = 0.5$ ).

*Choosing  $\alpha$ .* With the help of the matching vectors  $\mathbf{m}_i^\alpha$  the networks of our ensemble are placed in a space where distances between vectors correlate with structural differences of the corresponding networks. Besides the normalization, an important influence on this distribution is exerted by  $\alpha$ , which can be freely chosen. We examined the cases of  $\alpha$  being 0, 0.5 and 1 and chose the one that allows the best clustering for our purposes.

With the help of metric multi-dimensional scaling (MDS) we additionally visualize the influence of  $\alpha$ . This allows us to project the matching vectors into two-dimensional space where an impression of the distribution is given. Plots of projections of the ensemble with each matching vector as a dot are shown in Figures 2 and 3.

For  $\alpha = 0$  and  $\alpha = 0.5$  only clusterings containing one big cluster and several very small ones could be found. This is also supported by the plots in which all networks are concentrated around a single point and no obvious clustering can be seen. The situation is different for  $\alpha = 1$ , where only fractional group sizes are taken into consideration. Here already the plot indicates that the distribution is not concentrated around a single point, but reveals some structure in the ensemble. Since our aim is to find meaningful trends within the given ensemble, we concentrated on clustering with features weighted with  $\alpha = 1$ .

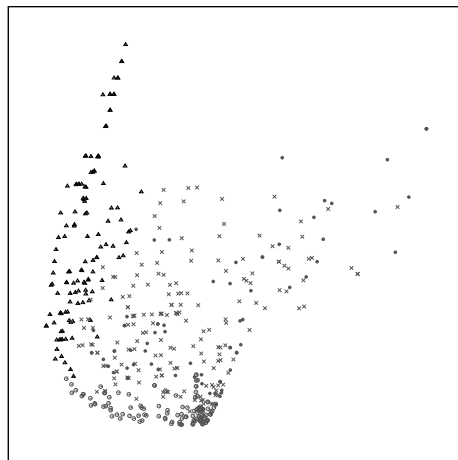


Figure 3: Plot of the ensemble based on class size ( $\alpha = 1$ ). A clustering is depicted by the different point types.

By varying the number of clusters in a reasonable range the silhouette coefficients shown in Figure 4 are obtained.

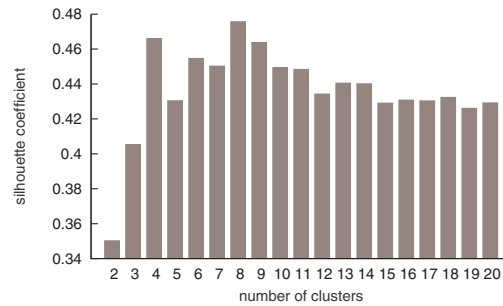


Figure 4: Plot of the silhouette coefficient for clusterings differing in the number of clusters. For each number of clusters the clustering was repeated 1000 times and the optimum in each iteration was used for comparison.

These hint at two different groupings that consist of four and eight clusters, respectively, and seem to conform to similarities in the ensemble better than the others. The resulting summaries are given in Figures 5 and 6

#### 4. Discussion

The classifications into four and eight groups are related to the modes of acculturation proposed in Berry (1997). These modes correspond to four distinct strategies reflecting two different aspects of the integration process an individual chooses (or is forced to choose) to cope with the situation of living in a new, foreign society. The two aspects are maintenance of an individual's identity and cultural characteristics, and maintenance of relationships to the larger society. In our interpretation the maintenance of individual characteristics is represented by contact to people having similar cultural backgrounds, thus alters from the origin and fellows classes. Consequently contact to the larger society is represented by alters in the host class or transnationals populating the personal network.

The four resulting extremal strategies or modes of acculturation are termed *integration* for maintaining both, individual characteristics and contact to the large society; *assimilation* for emphasis on contact to the new society while abandoning individual characteristics; *separation* for an emphasis on the maintenance of personal characteristics without seeking contact to the host society and *marginalization* for ignorance of both aims.

*Eight clusters.* We find a clustering with maximum silhouette coefficient having eight clusters containing 18 to 131 networks (see Figure 5). It is apparent that the clustering exhibits groups that are extreme with respect to class size distributions.

In clusters (b), (d), (f), and (h) one class of alters makes up at least 65% of the complete network. These can partly be seen as extreme instances of the aforementioned modes of acculturation. The networks in the very small cluster (b) for example seems to consist of transnationals only, these individuals seem to have nearly no contact to alters originating from the new host society nor can mentionable numbers of alters from the origin or fellows groups be observed. Since this cluster contains only 18 of 504 networks (about 3.6% of the ensemble) it could also be interpreted as a collection of outliers. Cluster (d) seems to be a perfect example of assimilation, since personal contact is limited to members of the host society. The clusters (f) and (h) are perfect examples for separation (nearly no contact to the host society at all) and marginalization (contact is limited to alters sharing the same origin). The other clusters represent mixtures of these extremes. The ones explaining most of the ensemble are the clusters (a) and (g), covering almost half of all networks in the ensemble and representing nearly opposite modes of acculturation. Cluster (a) shows a strong tendency for separation, expressed by nearly half of all the alters being origins while the contact to alters living in the host society is almost limited to people sharing the same origin and background. In these networks on average 4 out of 5 alters share the country of origin with the ego. In contrast cluster (g) could be seen as a collection of optimal integration examples. The egos of these networks have on average a high quality contact with the host society which is expressed not only by the size of the host group but additionally in the dense connectedness within this group. This implies an embedding in a group of persons that know each other - a necessary condition for a network of friends, rather than a collection of isolated contacts. At the same time these individuals maintain a considerable degree of contact to their original culture, showing in about one third of there personal contacts with people of the same cultural background (fellows and origins). Further the two classes of hosts and fellows are relatively well connected to each other, which can be interpreted as an integration between the two groups. Cluster (c) seems to represent networks

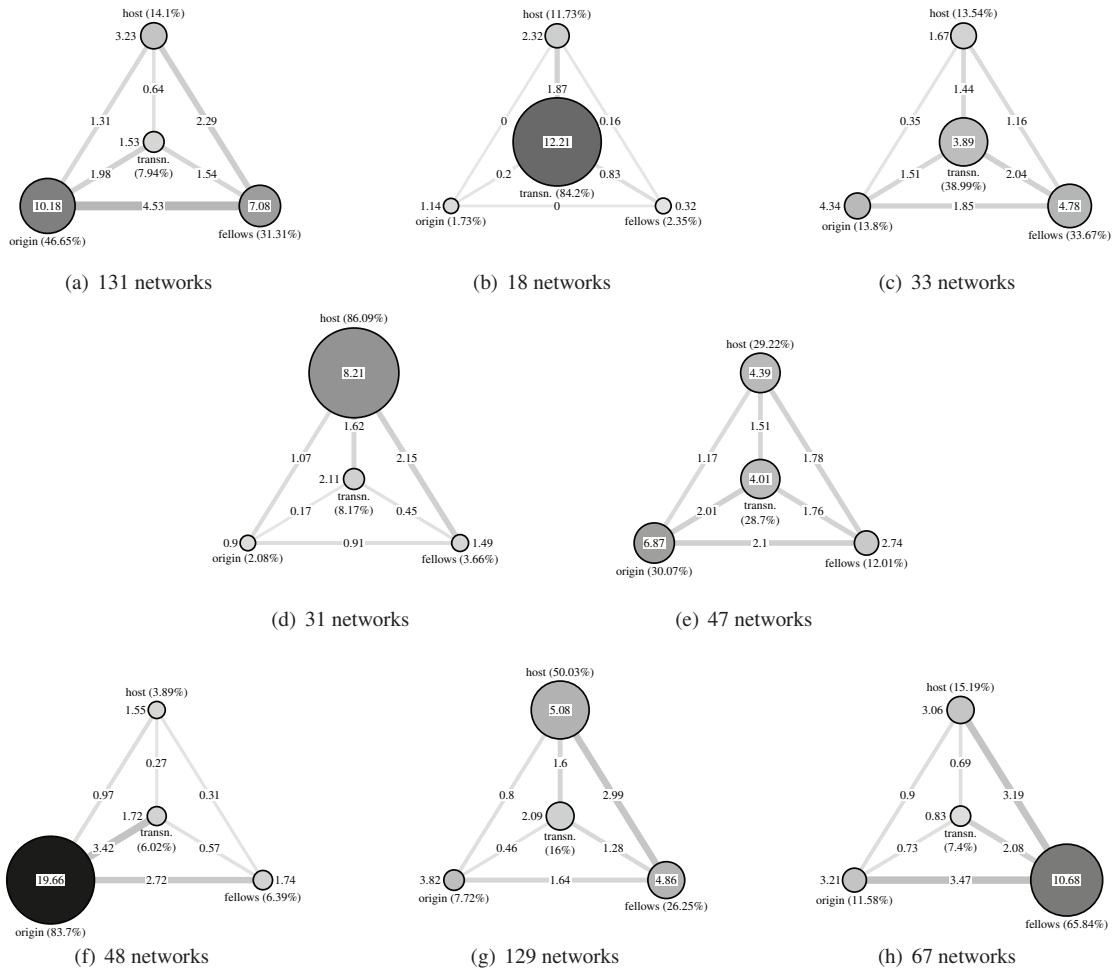


Figure 5: Role graphs for a partition into eight clusters of networks. Intra class average degrees appear inside of nodes, average degrees between classes appear on edges. The fractions of actors belonging to the positions is given in parenthesis.

suffering at least partly from marginalization. Though there is considerable contact to people of different backgrounds (altogether more than 50%) with transnationals being the largest group but the contact to people originating in the host culture is minimal. This could be due to technical reasons (i.e. sharing of flats). Together with cluster (b) which shows the same effect more prominently and the cluster in Figure 6(c) we have strong support that this is not a random artifact but a meaningful group of similar networks. A cluster representing nearly the total ensemble average is (e). It is hardly assignable to any of the typical modes of acculturation, and the small class of fellows compared to the relatively large class of origins is somehow irritating. A simple explanation is the lack of fellows in the host society, but also a transition of between two modes (from separation to assimilation) yields an interpretation. An example would be an individual that clearly follows the strategy of assimilation but is still in the middle of this process.

*Four clusters.* The partition into four clusters (see Figure 6), on the other hand, yields fewer outliers in class size, but also lacks the clear interpretability of most of the clusters of the clustering with eight clusters.

Nevertheless, the clusters match the proposed modes of acculturation almost exactly. The networks summarized in Figure 6(a) show strong separation, both with respect to nationality (most of their alters are born in the country of origin) and with respect to place of residence (most of their alters still live in the country of origin). The migrants giving rise to the networks summarized in Figure 6(b) know many people living in the host country but still show strong separation with respect to nationality since most of their contacts are classified as fellow immigrants. Figure 6(c) exhibits high levels of integration; while there is a considerable number of hosts (about 22%), the remaining alters in these networks are not concentrated on one of the distinguished groups but in the transnationals class. Networks



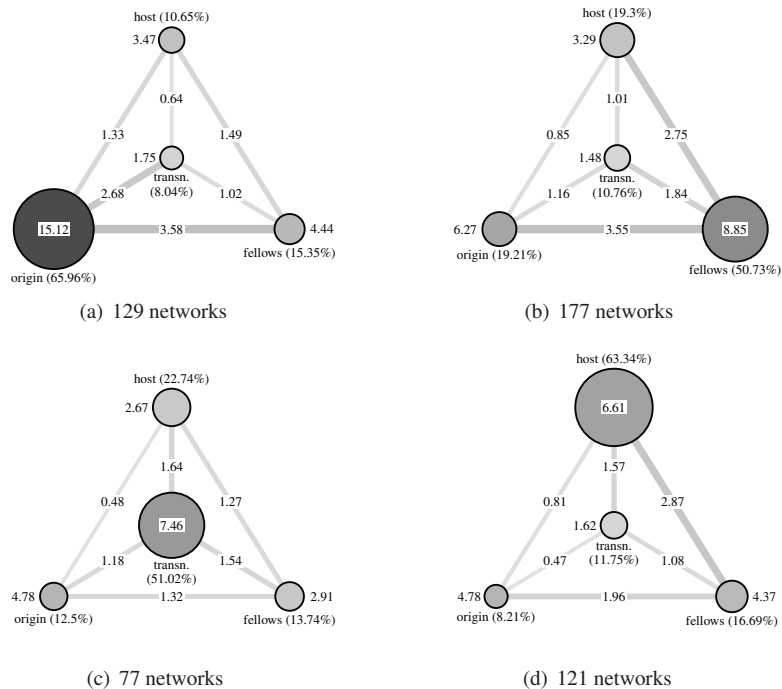


Figure 6: Role graphs for a partition into four clusters of networks. Intra-class average degrees appear outside of nodes, average degrees between classes appear on edges. The fractions of actors belonging to the positions is given in parenthesis.

classified into Figure 6(d) show strong patterns of assimilation since they know only few alters from their country of origin but most alters stem from the host society.

### 5. Summary and Outlook

We analyzed personal networks of migrants using a recent method which is able to detect and summarize groupings in an ensemble of networks. We further showed how to derive such a model from a given ensemble using class assignments of the nodes in the individual networks. Using feature vectors extracted from the structural description of the individual networks we clustered the ensemble into groups of structural similar networks. Finally, by using the obtained partition we achieved a more detailed description of the ensemble by deriving structural descriptions for the individual clusters. By variation of the number of clusters, we also enable a visual analysis of network ensembles with a variable level of detail. With the presented method we were able to show some general trends in a real world ensemble and empirically confirm some of the theory presented in Berry (1997).

*Outlook.* The presented work could be extended in two different directions, the analysis of the presented ensemble and the method of analysis itself. For the analysis it would be interesting to know, how the long members of different groups live in the country they immigrated to and if a relation to their situation with respect to acculturation can be shown. Also the use of other attributes for node classification would be interesting.

The extension and further development of the method itself has two different targets: provide better possibilities for the visual exploration of network ensembles and extend the possibilities of the model building process. In the model building process, especially the class assignments of the nodes is an interesting target of development. Currently this relies on the attributes of the nodes in the networks combined with expert knowledge. Eventually interesting class assignments in the ensemble can be derived from the fact that good clusterings of the node set are possible when the clustering is focused on certain attributes. This also would extend the possibility to explore ensembles for which no assumptions on the importance of individual attributes exist.

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