A Network Approach to Characterizing Personality in the Life and Time Longitudinal Sample

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Method

The Life and Time study collected a nationally representative sample of participants who completed multiple personality measures each year for four years. This analysis is restricted to BFAS items from participants who provided data at all **4 waves (N = 493, 155 males; age range = [18,55], M = 34.8, SD = 10.1)**

Item scores were calculated for each participant by taking the mean score from all four waves and then each item was scaled to have a mean = 0, and SD = 1. This use of longitudinal data resulted in high per-item internal consistency.

An adjaceny matrix describing relations between each item and all other items was produced using LASSO regularized regression to estimate coefficients for the following equation:

$$\mathrm{bfas}_1 = \beta_0 + \beta_{12}\mathrm{bfas}_2 + \ldots + \beta_{1j}\mathrm{bfas}_j + \epsilon_1$$

With the adjacency matrix defined as:

$$\begin{matrix} 1 & \beta_{12} & \cdots & \beta_{1j} \\ \beta_{21} & 1 & \ddots & \beta_{2j} \\ \vdots & \ddots & 1 & \vdots \\ \beta_{i1} & \cdots & \cdots & 1 \end{matrix}$$

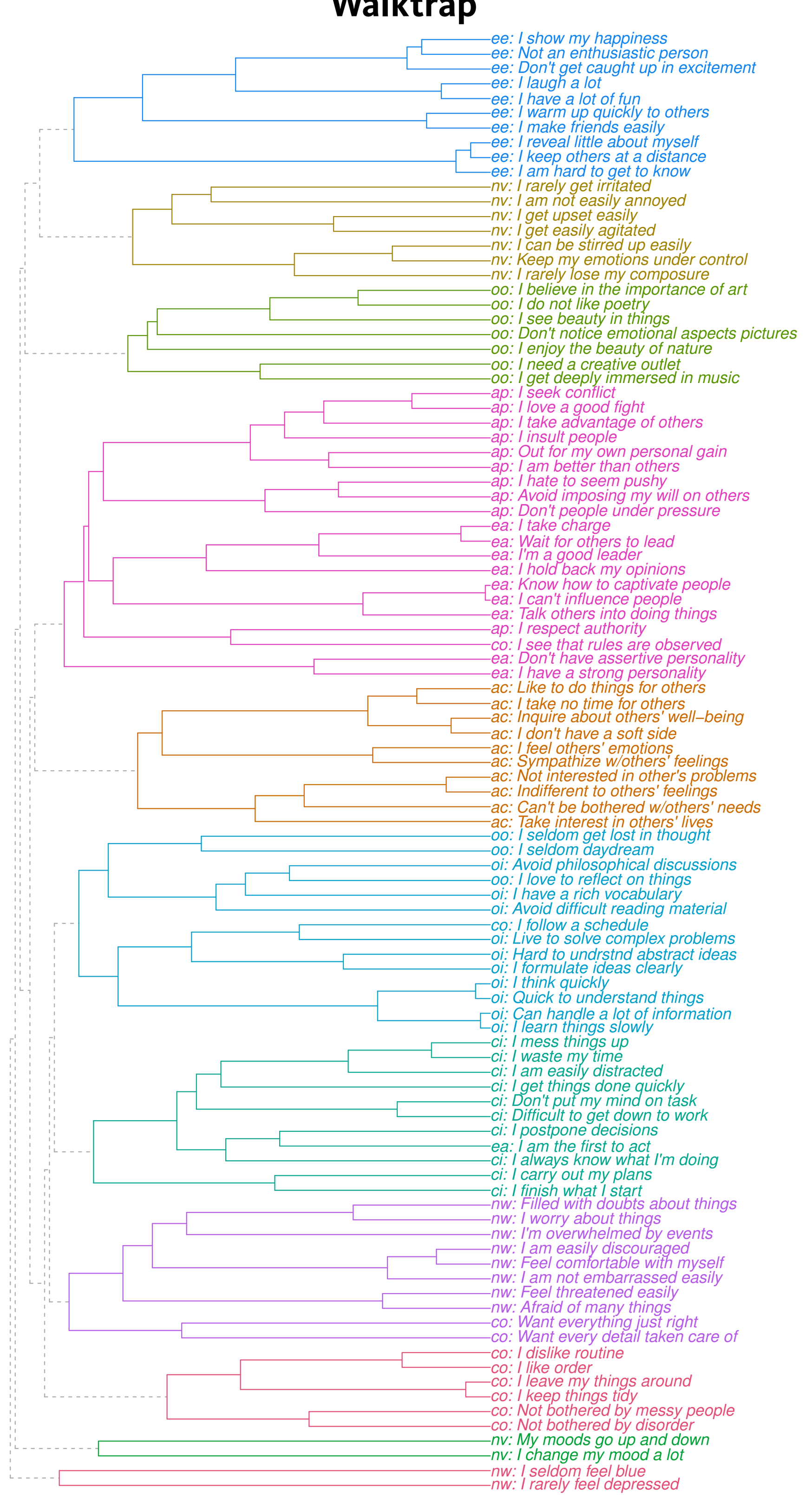
LASSO regression minimizes the sum of the squared errors, but also constrains the sum of the absolute value of the coefficients (using a constraint set by k-fold cross validation). This results in a more parsimonious network at the cost of downward bias.

Using the above procedure, an adjacency matrix was calculated for each of 1008 bootstrap samples from the original data. The graph to the right is defined such that the edge joining bfas item *i* and *j* is weighted with the median coefficient from all bootstrap estimates.

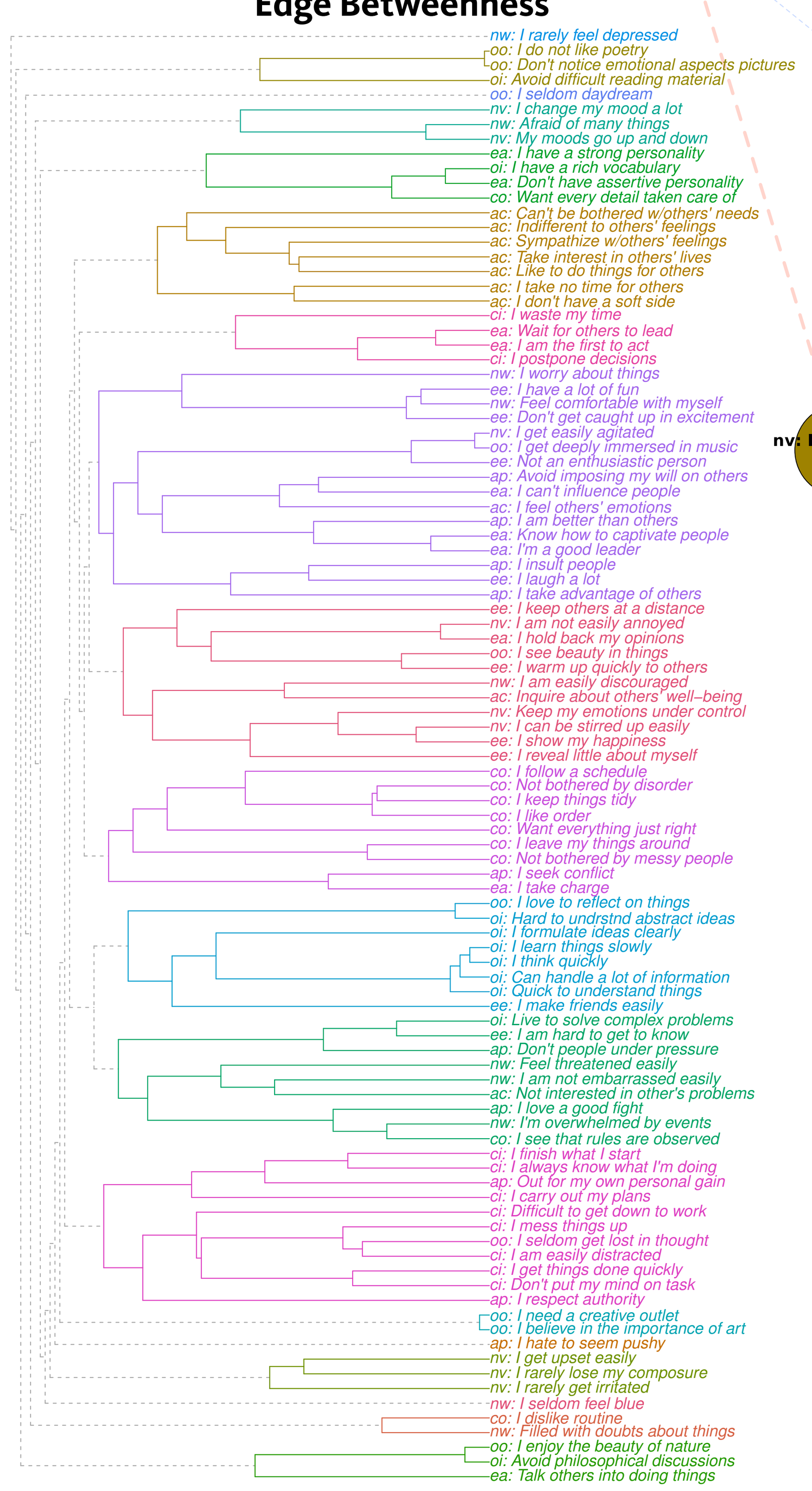
Finally, both edge-betweenness and walktrap algorithms were used to detect communities of BFAS items that were more densely connected to one another, than to other items. The **edge-betweeness** method finds communities by cutting edges with the highest number of shortest paths that pass through that edge. By analogy, it separates communities by finding the highways that are the only option for traveling between then. The **walktrap** algorithm performs random walks on the graph and groups nodes that are often part of the same random walk. This is based on the idea that one is more likely to wander within a community given the relatively fewer number of edges that lead outside of a community.

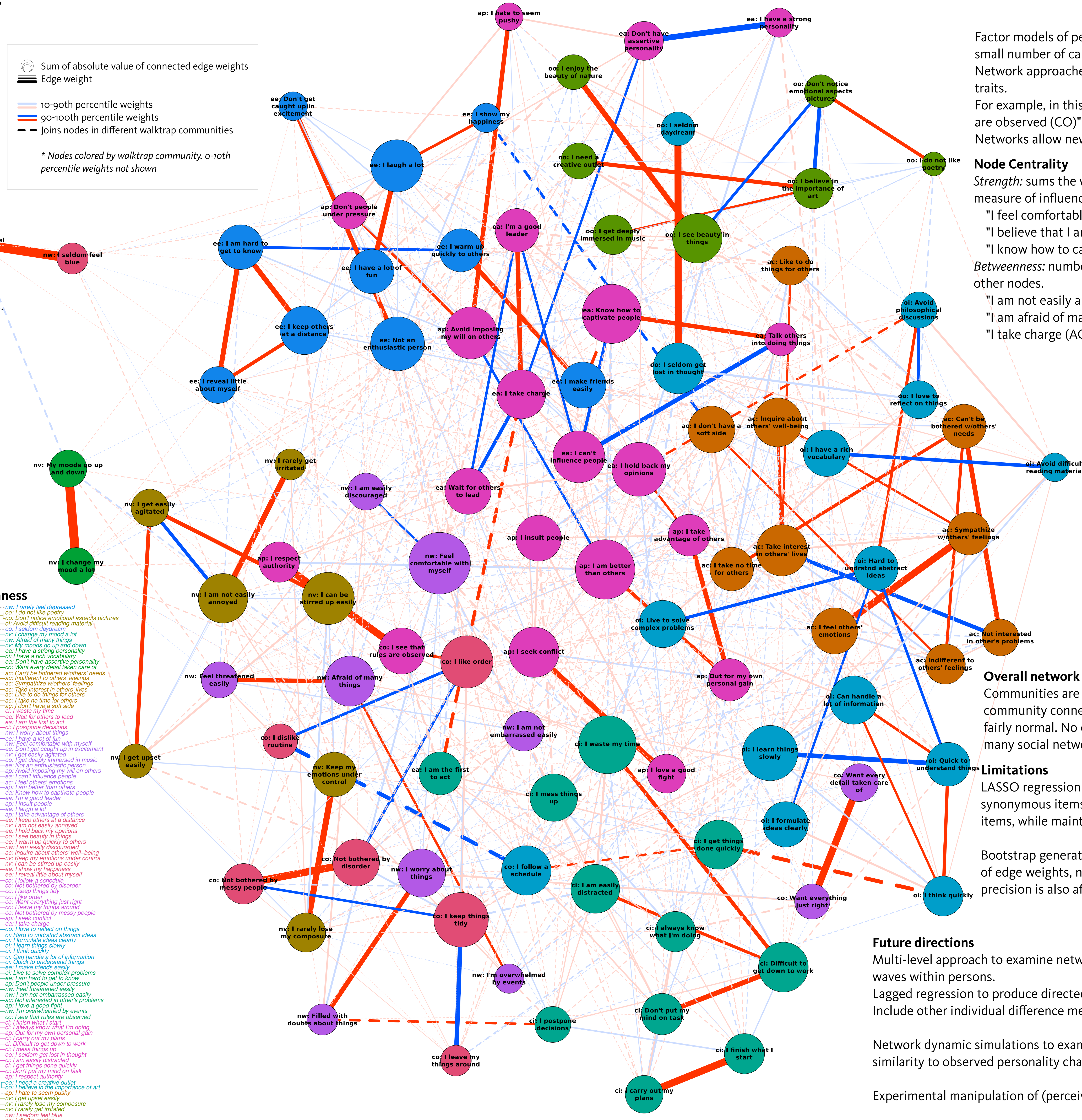
Community Detection

Walktrap



Edge Betweenness





Discussion

Factor models of personality posit that trait variances arise from a small number of causes that may or may not be correlated.
Network approaches allow for direct causal interactions between traits.
For example, in this network "I like order (CO)" <-> "I see that rules are observed (CO)" <-> "I respect authority (AP)".
Networks allow new kinds of description and inference.

Node Centrality

Strength: sums the weights of paths connecting to each node (a measure of influence on or by immediate neighbors).

"I feel comfortable with myself (NW)"
"I believe that I am better than others (AP)"
"I know how to captivate people (EA)"

Betweenness: number of paths that are the shortest route between other nodes.

"I am not easily annoyed (NV)"
"I am afraid of many things (NW)"
"I take charge (AC)"

Communities

Grouping items into communities based on network properties that may not be recoverable using E/CFA.

Walktrap resolves 10 communities (modularity = .40) that are somewhat reflective of the a priori big five factors and aspects, with important differences. One community consists of a mixture of EA and AP items; another community ties together symptoms of anxiety from NW and detail oriented items from CO.

Edge-betweenness produces 19 communities (modularity = .20). Many singletons, more heterogeneity.

Overall network structure

Communities are not well separated, with a lot of inter-community connections. Distribution of node strength, , is fairly normal. No evidence of small world properties that arise in many social networks.

Limitations

LASSO regression may be unduly influenced by nearly synonymous items. Raters may be able to group synonymous items, while maintaining granularity.

Bootstrap generation of adjacency matrices allows examination of edge weights, node and network statistics precision. However, precision is also affected by the presence or absence of nodes.

Future directions

Multi-level approach to examine networks defined by correlations among items over waves within persons.
Lagged regression to produce directed networks.
Include other individual difference measures, e.g. values, goals, behavior, physiology.

Network dynamic simulations to examine stable states, effects of perturbations, and similarity to observed personality change.

Experimental manipulation of (perceived) personality.