Network generation

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Rationale

We aim to assess network effects by embedding the teams in our simulation into different kinds of networks. This is intended to reduce the number of abstractions that the model entails, thus making the model slightly more "realistic", in that actual researchers are of course embedded into a network of social ties, and these ties have an effect on the researchers themselves.

The literature on co-authorship networks (see e.g., M. E. J. Newman (2004), M. Newman (2001), Kumar (2015)) generally finds them to exhibit dynamics of both small-world networks Watts and Strogatz (1998) and scale-free networks Albert and Barabási (2002). In plain language, co-authorship networks tend to comprise small groups of authors who collaborate frequently, with a few highly connected authors, who tend to be well-known and key figures in a community. Given that our model considers research *teams*, rather than *individual researchers*, we did not attempt to calibrate our networks against any given network, but rather to contrast networks with high and low clustering. This can be thought of contrasting research in the natural sciences, such as in physics, with research in the social sciences and humanities. As a baseline, we consider a random network.

Package setup

Baseline - random network

For the random network, we simulate a graph according to the Erdős–Rényi model in the $G(n, p)$ variant, with $n = 100$ and $p = 0.06$. The value for p was chosen to be as low as possible while still obtaining a fully connected network. Figure 1 shows the resulting network. Key summary statistics are provided in Table 1.

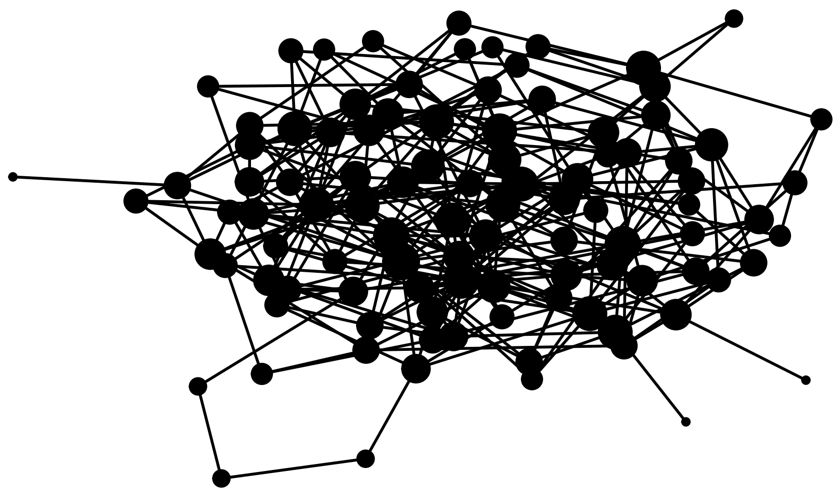


Figure 1: Random network. Node size corresponds to the node's degree.

Table 1: Summary statistics for random network

(a) We report the global clustering coefficient, that is, the number of closed triangles divided by all triangles in the network. This is not identical to the average local clustering coefficient.

Number of Nodes	Average degree	Clustering coefficient	Average path distance
100	5.66	0.044	2.818

Case 1: Low clustering

The first case of interest is a network with low clustering. The network is set up to exhibit traits of both small-world and scale-free networks. We simulate the network in three steps:

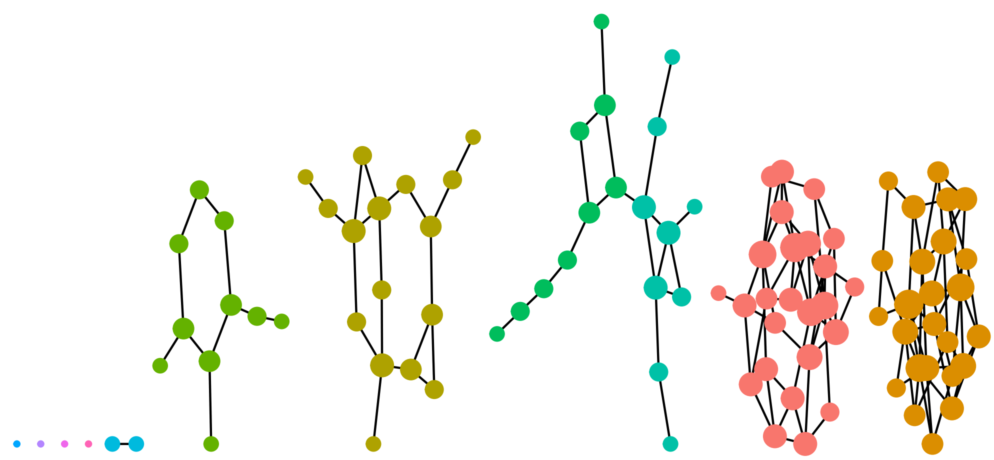
1. We first generate multiple small-world networks that resemble clusters or communities within the field of interest.
2. We add many edges to a few randomly picked nodes to create hubs. The edges are added by following the Barbasi-Albert algorithm:

    1. Pick a random node o.
    2. Pick a second node k from all nodes (except the node chosen in step 1), with probability $p(e)$, where $e = \frac{degree_k}{\sum_{i=1}^{k} degree_k}$
    3. Add one edge from o to k.

3. We remove any nodes that are not connected to the main component.
4. Add further nodes and edges according to the Barbasi-Albert algorithm to ensure sample size of $n = 100$.

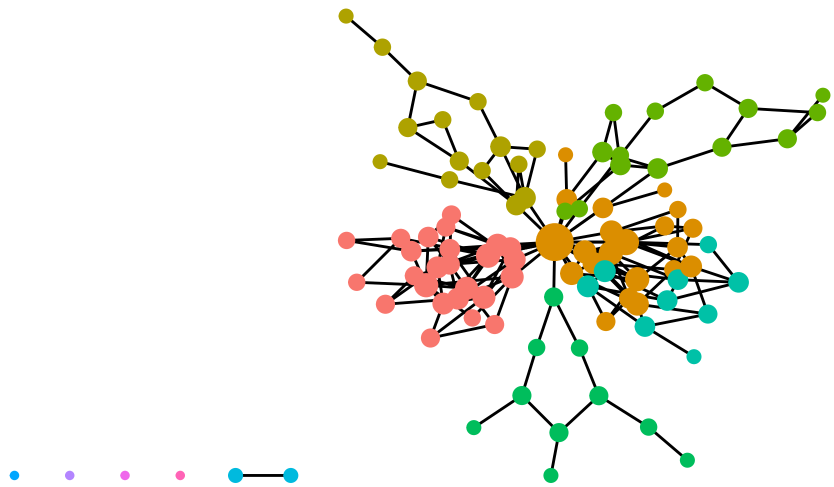
Step 1: create fragmented communities

The fragmented communities are generated using the small-world algorithm proposed by Watts and Strogatz (1998). We obtain low clustering by using small neighbourhood sizes (1-2), and a moderate rewiring probability (0.2-0.3).



Number of Nodes	Average degree	Clustering coefficient	Average path distance
100	3	0.198	2.706

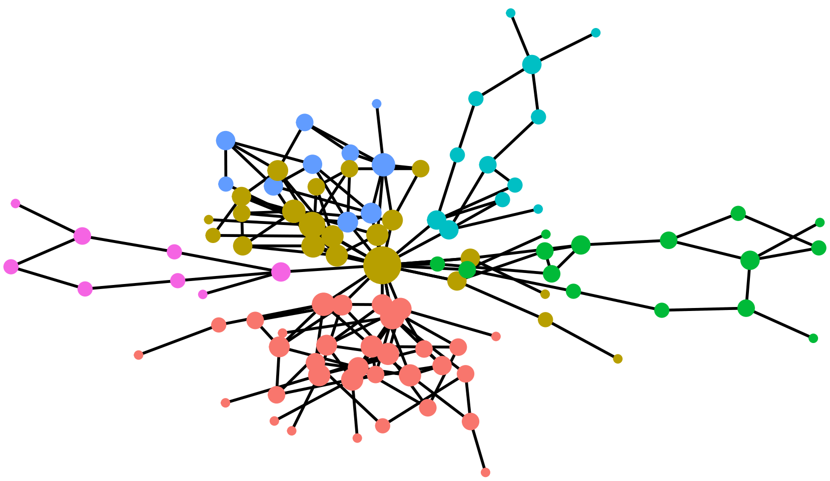
Step 2: add hubs



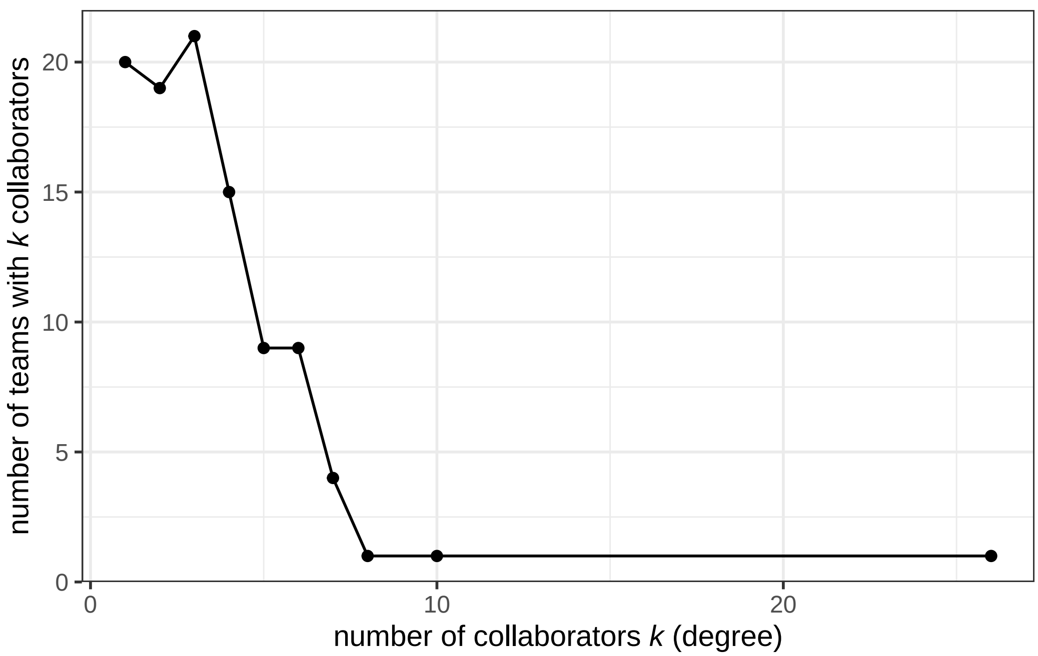
Number of Nodes	Average degree	Clustering coefficient	Average path distance
100	3.5	0.157	4.206

Step 3: Remove unconnected nodes

Step 4: Add nodes and edges



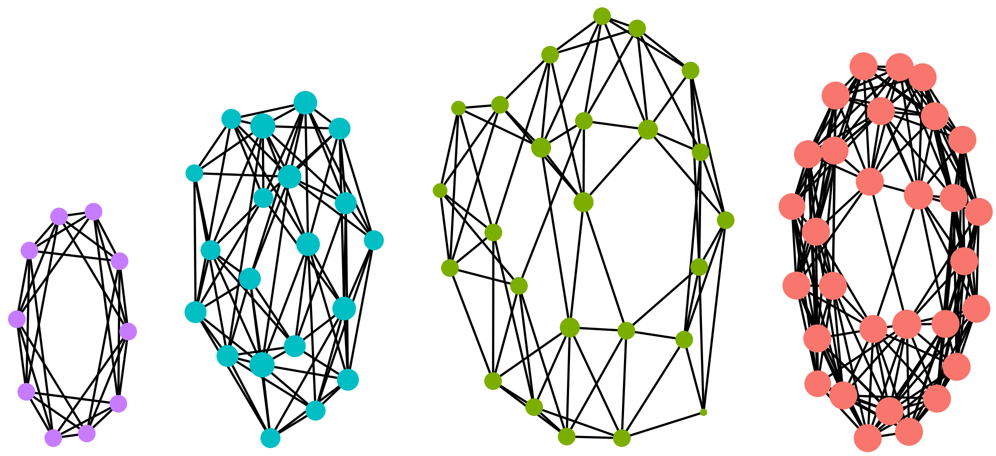
Number of Nodes	Average degree	Clustering coefficient	Average path distance
100	3.52	0.135	4.147



Case 2: High clustering

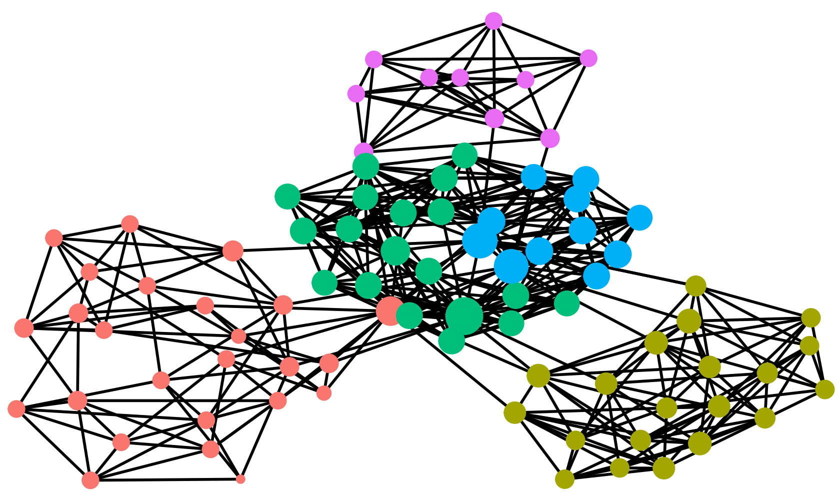
Step 1: create clustered communities

Highly clustered communities are obtained by using a larger neighbourhood size (3-6) for the clusters of 10-30 nodes, and setting a low rewire probability (0.01-0.05).



Number of Nodes	Average degree	Clustering coefficient	Average path distance
85	8.588	0.599	1.828

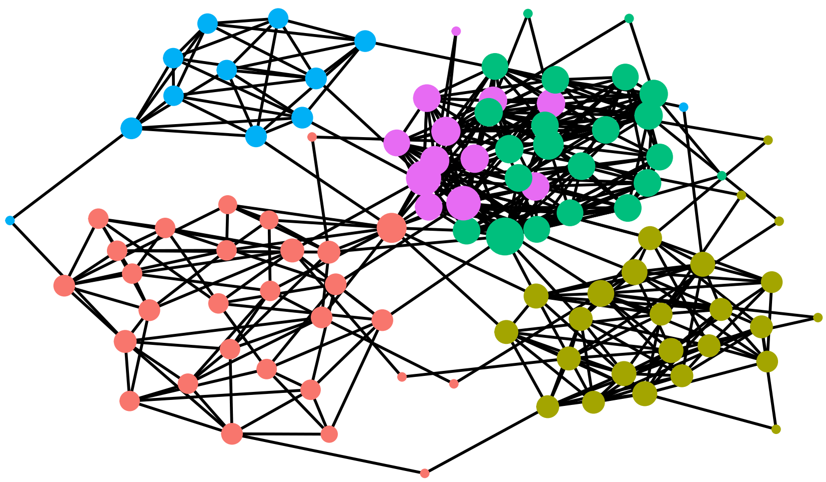
Step 2: add hubs



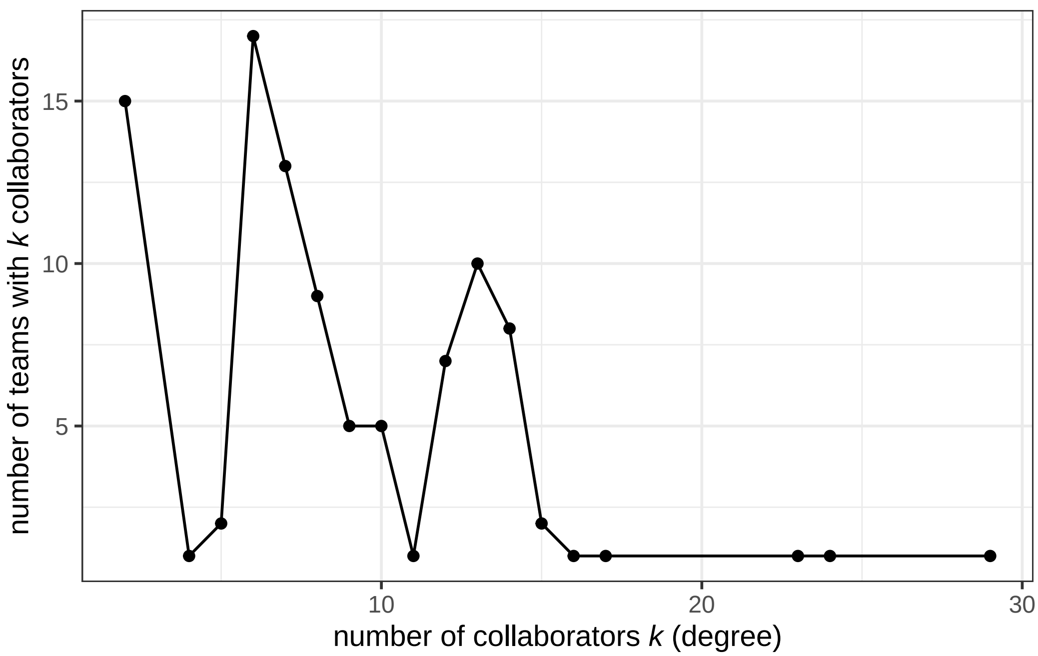
Number of Nodes	Average degree	Clustering coefficient	Average path distance
85	9.647	0.52	2.869

Step 3: Remove unconnected nodes

Step 4: Add nodes and edges



Number of Nodes	Average degree	Clustering coefficient	Average path distance
100	8.8	0.483	2.975



Summary of networks

Figure 2 provides an overview of all three generated networks. Network (A) is clearly random, with no apparent clusters and relatively similar degree across all nodes. In addition, the clustering coefficient is very low (see Table 8). This network serves as a baseline for our simulation.

Network (B) exhibits equally low clustering, but high path length and low degree. This resembles a community where most agents are not well connected, and the distance to other agents is sometimes long. Nevertheless, the network includes a few hubs which are much more connected than the other agents. This might represent a typical sub-field within the social sciences and humanities.

Network (C) is characterised by highly clustered communities, with high average degree, high clustering, and relatively short average paths. Hubs are present and connect the different communities, but are more similar to other nodes in terms of their degree than in the case of network (B). This network might represent a typical sub-field within the natural sciences.

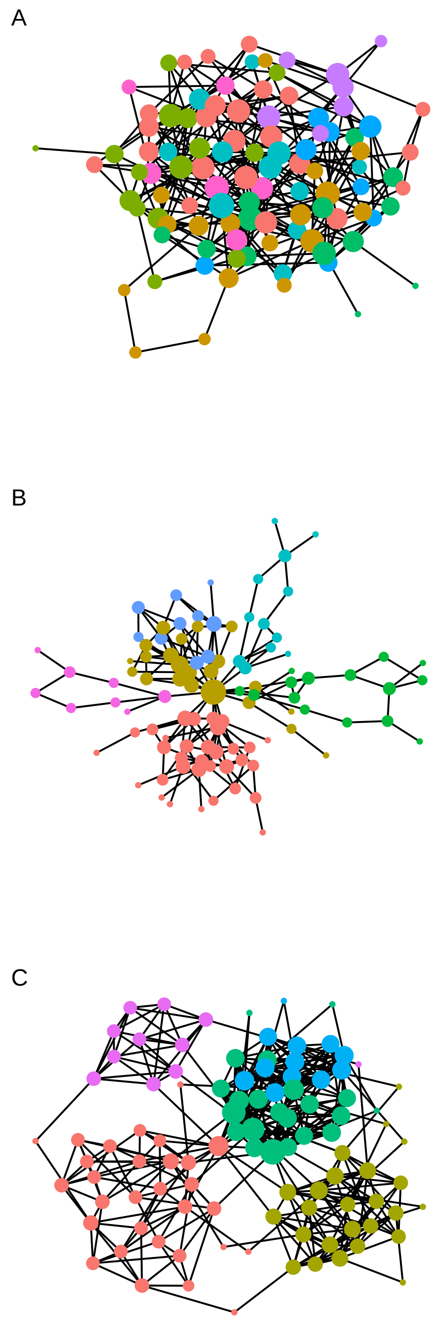


Figure 2: Overview of network topologies. (A) Random network. (B) Network with low clustering. (C) Network with high clustering. Colours represent groups optained via the Louvain algorithm. The size of nodes refers to their total degree.

Table 8: Network properties of generated networks

Topology	Number of Nodes	Average degree	Clustering coefficient	Average path distance
Random	100	5.66	0.044	2.818
Low clustering	100	3.52	0.135	4.147
High clustering	100	8.80	0.483	2.975

References

Albert, Réka, and Albert-László Barabási. 2002. "Statistical Mechanics of Complex Networks." *Reviews of Modern Physics* 74 (1): 47–97. https://doi.org/10.1103/RevModPhys.74.47.

Kumar, Sameer. 2015. "Co-Authorship Networks: A Review of the Literature." *Aslib Journal of Information Management* 67 (1): 55–73. https://doi.org/10.1108/AJIM-09-2014-0116.

Newman, M. E. J. 2004. "Coauthorship Networks and Patterns of Scientific Collaboration." *Proceedings of the National Academy of Sciences* 101 (suppl_1): 5200–5205. https://doi.org/10.1073/pnas.0307545100.

Newman, Mark. 2001. "The Structure of Scientific Collaboration Networks." *Proceedings of the National Academy of Sciences of the United States of America* 98 (2): 404–9. https://doi.org/10.1073/pnas.98.2.404.

Watts, Duncan J., and Steven H. Strogatz. 1998. "Collective Dynamics of 'Small-World' Networks." *Nature* 393 (6684): 440–42. https://doi.org/10.1038/30918.