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Beyond space and blocks: Generating networks with arbitrary structure

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CONTEXT

Random graph models are ubiquitous in network science. Often used as null models, they require to preserve the size of the observed networks, i.e., the number of nodes and edges. We focus on models in which the probability to observe an edge between each pair of node is independent, as in an ER or expected degree preserving (Chung-Lu) model. Such models are widespread for block structures (SBM) and spatial structure (e.g., Waxman, gravity model), but there is no simple solution to create random graphs with arbitrary —defined by the analyst— structures.

CONTRIBUTION

We propose a model allowing to generate graphs of a chosen number of nodes and expected number of edges, following an arbitrary structure, and with a controllable amount of randomness. The model requires:

STRUCTURE ZOO



LIRIS

- The number of nodes *n*
- The expected number of edges *m*
- A *cost function* describing the generated network's structure

Let's take a simple example: a possible cost function for a spatial graph is simply the distance betwen the nodes — This distance can be attributed randomly, or kept from observed data.

PROCESS OVERVIEW



Figure 3. The Structure Zoo. Matrix of node-pairs ranks for networks with 128 nodes. Darker colors correspond to lower ranks. For *Disconnected cliques*, we set m = 128 * 8. When involving spatial or clique positions, nodes are ordered according to this value.

EXAMPLE: FRACTAL STRUCTURES



(a) Fractal Root tree embedding

(b) Fractal Leaves tree embedding

Figure 4. Two methods to create fractal structures by embedding nodes into complete binary trees. In the example, we embed 6 nodes. In the simpler case, the probability to observe a graph in the resulting graph is proportional to the distance between the nodes in the tree.

SMALL WORLD EXPERIMENT

| R = Rank | P = Probability | M = Random | G = Generated |
|----------|-----------------|-------------|---------------|
| Function | Function | Graph Model | Graph |

Figure 1. Generating networks using the Structify-Net approach. A rank function defines an ordering between node pairs. A probability function is used to assign an edge probability to each node pair based on their rank in the ordering. This gives a Random graph model, that can be used to generate graph instances. Note how the same Rank function R1 can give 2 Random Graph Models using different Probability function P1 and P2, how the same Probability function P1 is used for two different Rank functions R1 and R2, and how multiple graphs can be generated from a single Random Graph Model.

PROBABILITY FUNCTION

We use a function allowing to tune the amount of randomness of the structure, $\epsilon \in [0,1]$. When $\epsilon = 0$, the structure is deterministically determined by the cost function. When $\epsilon = 1$, the network is an ER random graph. The function interpolates between the two using a Bezier function, as illustrated in Fig.2



(a) Bezier interpolation of the number of edges encoun- (b) The corresponding probability function, i.e., proba-

To illustrate the flexibility of this approach, we first reproduce the famous Watts and Strogatz experiment, on which a regular circular network is progressively randomized, leading to the apparition of a *small-world* structure. (We use a normalized short path index increasing with shortest paths, in order to compare different network structures)



(a) The proposed rank matrix. It has similarity with, e.g., the spatial one in Fig. 3
(b) The small-world profile. As expected, the short path index increases significantly while the clustering coefficient remains close to the original value when increasing randomness
Figure 5. Replicating the Watts-Strogatz experiment

SMALL WORLDNESS OF OTHER STRUCTURES

Following the same experimental process, we can observe how different structures behaves in term of clustering coefficient and short paths

| ER | blocks_assortative | core_distance | disconnected_cliques |
|----|--------------------|---------------|----------------------|
|----|--------------------|---------------|----------------------|

tered at a given rank

bility of observing an edge at a given rank

Figure 2. Example of probability functions for various values of ϵ . In this example, we set m = 128, n = 512





Figure 6. Small-World profiles of networks generated by generators of the *structure zoo*. **Blue** is clustering, **orange** is the short path index (lower values correspond to longer paths). We observe *super-small-world*, e.g., fractal-hierarchy, *anti-small-world*, e.g., nestedness, profiles similar to the Watts-Strogatz network, e.g., spatial or blocks assortative.