Largenet2: an object-oriented programming library for simulating large adaptive networks

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The largenet2 C++ library provides an infrastructure for the simulation of large dynamic and adaptive networks with discrete node and link states. The library is released as free software. It is available at http://rincedd.github.com/largenet2. Largenet2 is licensed under the Creative Commons Attribution-NonCommercial 3.0 Unported License.

The investigation of dynamical processes on networks has become a highly active research field, which addresses questions from a wide range of disciplines [2, 17]. One of the fundamental tools of "network science" [4] is computer simulation. Prominent examples include the study of the propagation of communicable diseases in networks of social contacts [e.g. 15], the emergence of consensus in networks of interacting agents [5, 24], or the evolution of cooperation among selfish individuals [18, 19].

Over the past decade in particular, *adaptive* networks have received a lot of attention. In this class of network models the network structure itself changes dynamically in response to the dynamics of its constituents [11, 12]. This creates a feedback loop between the dynamics on the network and the dynamics of the network itself, leading to emergent complex behaviour. For instance, adaptive-network models have been studied for social networks [23], opinion formation [8, 16, 25], epidemic spreading [13, 21], and collective motion [6, 14].

Dynamical processes in adaptive networks are typically specified in terms of a set of rules that locally transform a part of the network, e.g., update a node's state according to its neighbourhood or modify the local connectivity of a node [10, 26]. An example of such rules for an epidemiological model is shown in Figure 1. The transformation rules can be directly implemented in computer simulations. For stochastic models, they are typically applied asynchronously using Monte Carlo techniques such as Gillespie's algorithm [9].

In order to apply the transformation rules efficiently in simulations, the network subgraphs involved in a specific rule must be accessible at random, i.e., they must be located directly without resorting to an extensive search in the network. For instance, for the infection rule in Fig. 1 (top), efficient access to the links connecting S- and I-nodes in the network must be provided. Thus appropriate data structures representing the network are required which provide random access to the network nodes, links, and similar subgraphs, store properties such as node and link states, and allow for fast changes of the network topology.

Standard data structures used to represent networks (or graphs) in computer science are tailored towards the efficient implementation of certain algorithms, as for instance graph traversal, search, or finding shortest paths [20, 22]. In most cases, these algorithms work on static networks with a fixed topology, and efficient access to node and link states is usually not of major concern. Such data structures are therefore not suitable for the the simulation of large adaptive networks, whose structure changes dynamically and depending on the node and link states.

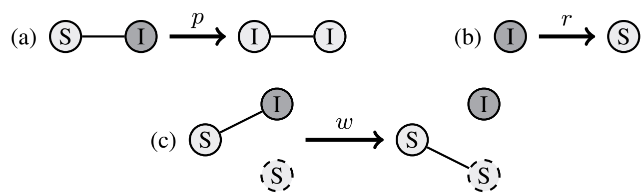

Figure 1. Diagrammatic representation of the transformation rules for an epidemiological model [13]. (a) a susceptible node (S) is infected through its link to an infectious neighbour (I) with probability p per S-I-link and unit time; (b) an infectious node (I) recovers with probability r; (c) a susceptible node (S) breaks its connection to an infectious neighbour (I) and rewires to another randomly selected susceptible node (dashed) with probability w. This last rule makes the network adaptive, because it changes the topology depending on the node states.

The *largenet2* library has been developed specifically for the efficient simulation of dynamic and adaptive networks. It provides data structures for networks with discrete node and link states (represented as integer numbers), allowing for fast random access to nodes and links in any given state, and efficient manipulation of these states and the network topology. Nodes, links, and, if required, larger subgraphs are stored in a custom-made, index-based container which can hold items in different discrete categories (states). It ensures that items in the same category are stored in contingent memory and provides both index-based and category-based access, so that selecting a random item in a given category can be achieved in constant time.

The network structure is modelled directly in memory using nodes and links as the basic entities in a double adjacency set representation, in which each node keeps a set of pointers to its incoming and outgoing links. At the cost of some memory overhead, addition and removal of links is thus achieved in logarithmic time. In effect, simulating large adaptive networks with *largenet2* is typically of linear complexity, i.e., the required simulation time scales linearly with the number of nodes in the network.

Additionally, the *largenet2* library provides a basic stochastic simulation framework implementing the original direct

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method of Gillespie's algorithm [9] and one of its variants [1]. The library consists of the following main packages, organized in different namespaces:

- network data structures for directed or undirected networks with or without parallel links (`largenet`)
- generation of random networks (`largenet::generators`)
- basic network measures, such as degree distributions and correlations (`largenet::measures`)
- network file input/output of edge list files and other file formats (`largenet::io`)
- stochastic simulation (`sim::gillespie`)

For implementation details, examples, and source code documentation, please refer to the website.

The *largenet2* library and its predecessor *largenet* have been used for the simulations of large adaptive networks in [3, 7, 27, 28]. To implement more complex transformation rules than depicted in Fig. 1, the library can be and has been extended to also track larger network subgraphs, such as node triplets, involved in such rules [e.g. 6, 14].

The open source library *largenet2* is under ongoing development. It is set up as a community effort and contributions are welcome at http://github.com/rincedd/largenet2.

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