Network Generation Model Based on Evolution Dynamics To Generate Benchmark Graphs

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Abstract Network generation models provide an understanding of the dynamics behind the formation and evolution of different networks including social networks, technological networks and biological networks. Two important applications of these models are to study the evolution dynamics of network formation and to generate benchmark networks with known community structures. Research has been conducted in both these directions relatively independent of the other application area. This creates a disjunct between real world networks and the networks generated to study community detection algorithms.

In this paper, we propose to study both these application areas together i.e. introduce a network generation model based on evolution dynamics of real world networks and generate networks with community structures that can be used as benchmark graphs to study community detection algorithms. The generated networks possess tunable modular structures which can be used to generate networks with known community structures. We study the behaviour of different community detection algorithms based on the proposed model and compare it with other models to generate benchmark graphs. Results
suggest that the networks generated using the proposed model present tougher challenges for community detection algorithms due to the topological structure introduced by evolution dynamics.

**Keywords**  Complex Networks, Network Models, Graph Generation, Community Structures, Benchmark Testing

1 Introduction

The world is full of connected systems represented by networks such as networks of social relationships [38], networks of chemical reactions [40], and networks of power grids [2]. A network can be of tangible objects such as a network of web pages, a network of Internet routers [11] and a network of highways [17]. It is also possible to define a network with entities that are defined in abstract spaces such as a networks of friendship and human sexual relationship [6].

The field of network analysis became popular from the late 1990’s after the ground breaking discoveries of structural characteristics of small world [42] and scale free networks [3]. Since then, researchers have actively pursued the development of network generation models to mimic the creation and evolution of complex networks emerging from a variety of real world interconnected systems. These models also provide an understanding of the many other common characteristics besides small-world and scale-free properties like assortative mixing, presence of hierarchical structures, presence of communities and likelihood of connection between similar objects. There is a substantial interest in using these synthetic networks to examine the impact of different dynamic processes on these networks like epidemic spreading [30] [25], information diffusion [14] and influence mining [18].

Two important application areas of these network models are in the study of evolution dynamics and in generating benchmark networks to study community detection algorithms. Evolution dynamics are important because they help us understand how real world networks attain certain structural properties. For example, triadic closures explain the presence of high clustering coefficients, preferential attachment explains why degree distributions follow power-law. The study of community detection algorithms help us determine the quality of a community detection algorithm which in turn, helps us determine how best to select and apply an algorithm given a network.
Many real-world networks belong to different domains and their topological and structural features make these networks different from one another. A co-authorship network of collaboration inducts cliques representing a set of authors strongly connected to each other whereas a social network introduces nodes gradually as new members sign up. This suggests that the underlying mechanism through which these networks evolve, (or simply the evolution dynamics) shape the structural and topological properties of a network. Figure 1 demonstrates the results studying building blocks of two networks from different domains. The authors diagrammatically show the differences in topological features between a co-authorship network and an air transport network.

Thus we argue that models to generate benchmark graphs should consider well known evolution dynamics to generate networks with known community structures. Since the performance of community detection algorithms vary with networks of different topological features, having a tunable model will also help us generate networks with desired structural features and thus can be used to evaluate the performance of community detection algorithm on a wide variety of structurally different networks.

Fig. 1. Building blocks of two different networks extracted at 5% of their maximum degree by using Maximum Edge Distribution [48]. A) Collaboration network of astrophysics archives (16706 nodes) [24] where an edge represents a collaboration between two authors. B) Air transportation network (1540 nodes) where edges represent a flight from one airport to another airport [35]. It is clearly visible that building components of both networks are different. Collaboration network decompose into a number of cliques which is different from the air transport network. This is due to the fact that a new instance in collaboration network may form of a clique of authors whereas for air transport network, a new instance is supposed to be an airport with number of flights connecting to other airports.
One of the earlier works for generation of synthetic networks with ground truth communities is by Girvan and Newman [13], which is commonly known as GN benchmark. Lancichinetti and Fortunato [20] identified a number of drawbacks in GN benchmark and presented a model to generate synthetic networks of different sizes with desired degree distributions and clustering. The model also provides a mechanism to generate networks with sparse or dense communities. However, it does not consider any dynamics or microscopic rules to generate networks. A number of models are available in literature to generate synthetic networks with presence of community structures based on different microscopic rules. Although networks generated by these models possess modular structures, they do not provide the mechanism to generate ground truth communities and ultimately cannot be used to produce benchmark graphs.

This paper is organized as follows: In Section 2 the current work available in literature for generating benchmark graphs along with the number of models that generate synthetic networks with community structures are discussed. Section 3 describes the proposed model and its parameters whereas section 4 lays down details about the experimental setup. Section 5 contains the results of those experiments whereas the conclusion of the paper with discussion on possible future directions is discussed in section 6.

2 Related Work

Benchmark Graphs

There are two approaches to evaluate the performance of community detection algorithms. The first approach is to test against real-world networks with prior information about communities and the second approach is to test against synthetically generated networks with ground truth communities [26]. Community detection algorithms which use the first approach have to rely on small networks such as Zachary’s karate club [46] and the college football network [16] due to unavailability of ground truth for large networks.

Yang and Leskovec [45] studied few large networks and identified their ground truth communities based on their nodal attributes. It has been observed that real-world networks behave differently for different definitions of communities due to inherent structural differences specially when nodal attributes are used to cluster nodes as compared to structural characteristics. Hric et al. [16] found significant differences between ground truth communities and
the communities identified by community detection algorithms in real-world networks.

In the second approach, the community detection algorithms are tested against synthetic networks generated by network models. The models used for this purpose must be capable of generating ground truth communities alongside the network in order to compare the results produced by community detection algorithms. Although, there are a number of models available in literature to produce synthetic networks with community structures their generation processes and mechanisms make it difficult to generate ground truth communities. The next subsection discusses some of these models.

The earliest and most famous work in this direction was introduced by Girvan and Newman which is known as the GN benchmark or ‘four-groups’ networks [13]. This model generates a network with 128 nodes divided into four groups i.e. 32 nodes are generated in each group where the average degree of each node is 16, which is close to the random graph of a similar configuration. In contrast to random graphs, the inter-cluster and intra-cluster connectivity of each node can be controlled by a parameter. A good community algorithm should be able to identify four separate communities generated by the model with a higher value for intra-cluster degree. Danon et al. proposed a variant of GN network to introduce communities of different sizes but those networks still do not mimic real-world networks with community structures due to their small size and the absence of fat tails in their degree distributions, which is observed in most of real-world networks.

Lancichinetti et al. proposed another model to generate benchmark networks, known as LFR benchmark, that can generate networks with heterogeneous degree distribution following power law. This model is capable of generating networks of large sizes with communities of different sizes and is capable of generating networks with different topological properties such as degree distributions and average degrees [22]. The size of communities can be specified by defining the minimum and maximum size of each community where the size of communities can also follow power law distribution. Lancichinetti and Fortunato also extended this model for overlapping and directed communities [20]. The model focussed on generating specific networks with desire characteristics but did not define microscopic rules during the formation of networks. The major drawback of this model is the absence in using evolution dynamics during the generation process. This motivated us to propose a new model which
incorporates well studied microscopic rules to generate networks.

Network Models with Community Structure

Since the discovery of the ground breaking small-world \cite{42} and scale-free \cite{3} networks, a number of network models have been proposed by scientists which are either variants or extensions of these two models. Early models were targeted to generate networks exhibiting properties of small-world and/or scale-free networks with low average path lengths, high clustering coefficients and degree distributions following power law. With the recent studies, other network structural properties have also gained importance and hence new generation models with these characteristics are also being proposed by scientists.

The primary purpose of these models is to generate synthetic networks to mimic the real-world networks. These models also help provide an understanding of the dynamics behind the formation of real-world networks. The presence of fat tail behaviour in real-world networks is due to the preferential attachment phenomenon which suggests that a new node tends to have a connection with an existing node having more connections. The benchmark graphs discussed in the previous sub-section do not consider these dynamics while discussing the generation of networks. There are numerous models existing in literature that generate synthetic networks but this paper limits the discussion to models with community structures.

Xu et al. \cite{44} extended the Barabasi-Albert model by introducing global random attachment for community selection whereas preferential attachment is used for the selection of nodes similarly as in the BA model. The basic idea is to first select a community randomly from the existing communities in the network followed by the selection of a node on the basis of preferential attachment. The model also creates inter-community and intra-community edges with some probabilities. The authors are able to generate networks with general power law distribution of nodes’ degree with the presence of community structures in the network.

Xie et al. \cite{43} proposed an evolving model based on preferential mechanism for the selection of communities and nodes to generate networks with community structures. They achieved the power law distribution for node degrees and the size of communities. Communities of larger sizes are preferred at the time of selection of a community, and a high degree node is preferred to select neighbours to create
inter-cluster edges. A similar model was proposed by Zhou et al. [50] for weighted evolving networks with additional triad formation step to achieve high clustering in generated networks. Both models allow the introduction of a fully connected community or a single node into the network with some probabilities.

The model by Kumpula et al. [19] is based on microscopic rules from sociology to generate networks with moderate size communities. They used cyclic closure and focal closure which are proven mechanisms in sociology to acquire new acquaintances in social networks. Random walk is used to achieve cyclic closures in order to find strong ties in the neighbourhood of a node whereas focal closure is achieved by formation of links with random nodes in network. They used a node deletion process to correspond with the scenarios in a real-world network when a person leaves a network.

Zaidi [47] discussed the role of randomness in the generation of community structures in a network. They introduced different sizes of closely connected communities by replacing nodes in a network generated by the ER model [10]. The authors found that by introducing a small order in random networks, we can generate clustered networks. However, networks generated by this approach do not have the scale-free property which is observed in many real world networks.

The model proposed by Sallaberry et al. is similar to configuration models such as Generalize Random Graph Models as it generates a network for the given degree distribution. However, the model generates cliques for the given degree distribution and creates connections among these cliques on the basis of distances among them [36]. The model is static in the sense that a number of nodes remain constant once degree distribution is assigned to nodes.

Recently an extension of Holme and Kim’s [15] was proposed by Pasta et al. [29] which is based on global random selection of a community and local preferential attachment for the selection of a node. The authors achieved three important structural properties that are high clustering coefficient, presence of hierarchical community structure, and each community following power law distribution for nodes’ degree.

The model proposed by Zaidi et al. [49] utilizes the concept of social ties, homophily and extraversion-introversion. The model suggests that there are a number of communities of different sizes in the world and these communities may overlap as one individual may belong to different communities simultaneously. However, with some randomness the people connect
to each other which results in the formation of large networks consisting of topologically different communities.

As we discussed earlier, to evaluate the performance of a community detection algorithm, the knowledge regarding which node belongs to which community is crucial. These models use different microscopic rules to generate networks with different topological structures but do not provide information about ground truth communities i.e. they generate networks with the presence of communities in networks but the information about nodes and the community they belong to is not preserved or generated by these models. Hence these models cannot be used as the benchmark.

On one hand, the benchmark graphs, like GN and LFR, generate networks to achieve global structural properties without considering microscopic rules. On the other hand, the models based on microscopic rules and evolution dynamics to generate networks with community structures do not preserve information about ground truth communities. To address this issue, we proposed a growing model based on well known evolution dynamics and microscopic rules: global community selection and local preferential attachment to generate networks with ground truth communities. This model extends the model [29] which itself is an extension of the seminal BA [3] model.

3 Proposed Model

The proposed model uses two microscopic rules, global community selection and local preferential attachment to generate a network with the presence of community structures. The model comprises of similar steps as the original model proposed by Pasta et al. with additional heuristics to decide over the community of each node. A mixing parameter ($\mu$) which ranges between 0 and 1 is introduced. This parameter determines the quality of modular structures in the network. Lower value of $\mu$ results in well separated communities and vice versa.

Each new node has $\mu$ fraction of edges with nodes belonging to the same community whereas $1 - \mu$ edges with nodes belonging to other communities. However, it does not guarantee that each node will have the exact fraction of edges within or outside the community. The rest of the parameters include: number of nodes in network ($N$), number of communities in network ($\varsigma$), probability of triad formation($P_t$), number of edges for each new node($m$) are borrowed from the original models and details of which can be found in [29].

The model comprises of two major phases:
**Setup:** We introduce triads in network - same as the value of the required number of communities ($\varsigma$) in the network. Each triad represents a community and each node of the respective triad is labelled with a number representing its community.

**Grow:** The following steps repeat until $N$ new nodes are introduced in network

1. At each timestamp $t$ a new node $n$ is introduced to the community and connected to an existing node $n'$ selected on the basis of preferential attachment. At this stage the community of node $n$ is assigned to node $n'$ as well. Thus, both nodes now belong to the same community and have similar labels.

2. With probability $P_t$, node $n$ creates $m$ edges with neighbours of $n'$ whereas fraction $1 - \mu$ edges are connected to neighbours which are not part of the same community and a fraction of $\mu$ edges are created with the neighbours of the same community.

3. Similarly, $m$ edges are created preferentially with probability $1 - P_t$ whereas fraction $\mu$ edges connect to nodes from the same community while a fraction $1 - \mu$ edges are connected to nodes of other communities.

### 4 Experimental Setup

The models presented in literature for the generation of synthetic networks are tested against social network analysis measures like degree distribution, clustering coefficient and geodesic distance to evaluate the structural and topological properties of networks [1]. The benchmark graphs with ground truth communities are evaluated to test how well defined communities exist in the network. As the proposed model intends to generate benchmark graphs but based on microscopic rules, the interest remains to: evaluate structural properties, quantify how good communities are generated, and evaluate the performance of community detection algorithms on networks generated by the proposed model.

The proposed model was tested for different configurations of four controlling parameters as described below. The parameter to control number of edges for each new node ($m$) is fixed to 2 for all configurations. We produced 240 graphs and the results are averaged over 5 instances for each of the configuration to reduce biasness because caused by randomness.

**Networks Size ($N$):** determine the number of nodes in network. Networks of 1000, 2000 and 4000 nodes were generated.
Number of communities ($\zeta$): controls number of communities in network. Networks for 10, 20, 30, and 40 communities were generated.

Probability of Triad Formation ($P_t$): controls the overall clustering in network. Higher value of this parameter will result in high clustering coefficient and vice versa. The model was tested for values of 0.1, 0.3, 0.5, 0.7 and 0.9.

Mixing Parameter ($\mu$): determines the fraction of edges of a node connected with other nodes of the same community. The lower value of this parameter will result in networks with clear separable communities. For this parameter networks with values of 0.2, 0.4, 0.6, and 0.8 were generated.

The two major benchmark graphs used to measure performance of community detection algorithms are GN [13] and LFR [20] benchmark graphs. Nowadays larger graphs with more than 128 nodes are available which is the limitation of GN benchmark to generate graphs of maximum size. However, the LFR benchmark can generate graphs of arbitrary sizes for desirable structural properties. For each graph produced by our model, graphs were generated by the LFR benchmark as well for similar structure properties such as average degree, degree distribution, and community sizes for comparison purpose.

4.1 Goodness of Community

Despite the fact that community detection is one of the widely studied problems in network science but there is no single agreement on definition of community. Thus, testing a benchmark for a specific definition of community may lead to a situation in which a benchmark does not provide consistent results for all community detection algorithms. The proposed model was tested against different definitions of communities such as separability, density, clustering coefficient and loyalty.

Separability: Separability defines that a community must be well separated from the rest of the network i.e. a good community must have a lower number of edges pointing to nodes outside it’s community [37]. This can be quantified as the ratio between the number of edges inside and outside the community. Let $C$ be the community in consideration, $V$ as the set of nodes and $E$ is the set of all edges, we define separability as:

\[ f(C) = \frac{|\{(u,v) \in E : u \in C, v \in C\}|}{|\{(u,v) \in E : u \in C, v \notin C\}|} \]  

Density: Another perspective used to de-
fine communities is as dense components in networks. Density quantifies the fraction of edges which are part of the same community from all possible edges \([12]\). The more edges within a community suggests a good community - regardless of the number of edges pointing to nodes of other communities. Here \(n_c\) is the number of nodes in community \(C\).

\[
f(C) = \frac{|\{(u, v) \in E : u \in C, v \in C\}|}{n_C(n_C - 1)/2} \tag{2}
\]

**Clustering Coefficient:** Another definition of community is the components in networks in result of close binding with neighbour nodes which can be quantified as clustering coefficient \([42]\). A set of nodes with high clustering coefficient is a better community than a set of nodes with a low clustering coefficient.

**Loyalty:** We can define loyalty of a node as the fraction of edges of a node connected to nodes of the same community. A community with disloyal nodes suggests that community has more edges to an outside community than the inside community. The loyalty of a community is the average loyalty of all nodes of the community.

\[
f(C) = \frac{|\{(u, v) \in E : u \in C, v \in C\}|}{|\{(u, v) \in E : u \in C, v \in V\}|} \tag{3}
\]

The Separability and Loyalty both capture the same intuition that a community must be separated from the rest of the network but Loyalty quantifies this in a range of 0 and 1. This makes it easier to compare the results of two distinct sets of communities generated as a result of different community detection algorithms. In case of singleton communities when each node consists of only one node, the loyalty of each node will be 0. In the case of only one community, when each edge of each node points to the same community then the value of loyalty will be 1.

### 4.2 Community Detection Algorithms

The presence of community structures is one of the most important characteristics of real world networks. Finding communities in a network is a difficult but crucial task to understand the internal structures of a network. This has been a widely studied area by scholars of different domains and a number of algorithms have been proposed to detect communities in networks.

In order to cover a wide spectrum of community detection algorithms, eight community detection algorithms were selected for the experiment carried out in this paper and each algorithm represents a distinct class of commu-
nity detection algorithms. The selected algorithms are: Fast greedy clustering by Clauset et al. is a modularity optimization algorithm [7], Multilevel clustering which is an extension of modularity optimization with additional steps to merge found communities into a single node to repeat the same process [5], Walktrap by Pons and Latapy which is based on random walks to calculate distances between nodes in order to group them in one cluster [31], Markov Clustering (MCL) by van Dongen which uses markov matrices to simulate stochastic flow [39], Infomap clustering which solves the community detection problem using Information Theory [34], Label Propagation which only uses network structure without any prior information about communities or any objective function [32], VOS which uses the network layout approach to determine communities [11], and Spinglass based on the statistical mechanics’ spin models [33]. The detailed review of community detection algorithms is out of scope for this article and we encourage readers to refer respective citations for further details or [4] [23] [28] for comparative analysis.

The performance of these eight algorithms on networks generated by LFR benchmark and the proposed model were evaluated. There are a number of criterion available to compare ground truth communities with results generated by community detection algorithm. This paper used the most commonly used measure Normalized Mutual Information (NMI), in which the value is equal to 1 when two partitions are identical to each other, whereas it has an expected value of zero when partitions are dissimilar to each other [8].

A number of attempts were made to compare the performance of community detection algorithms on networks of small sizes [4], to understand structural properties [23] [28], or on benchmark which do not consider microscopic rules in the generation of networks [21] [22]. The interest of this paper was to compare the performance of community detection algorithms on the proposed benchmark which is based on widely accepted microscopic rules such as preferential attachment and triadic closure with conventional benchmark which do not consider microscopic rules in generation of networks.
5 Results and discussion

(a) Impact of network size \((N)\) and Probability of Triad Formation \((P_t)\) on Average path length of network

(b) Impact of network size \((N)\) and Probability of Triad Formation \((P_t)\) on Clustering coefficient of network

(c) Degree distribution of generated networks with different parameter of mixing parameter \((\mu)\)

Fig. 2. Structural properties of networks generated by proposed model.
The results and findings are presented as below. Initially, we study the quality of networks produced in terms of network metrics. Next we evaluate the quality of of communities generated by the model against different definitions of communities as discussed in Section 4.1. Then a comparison of performance of community detection algorithms for networks generated by the proposed model with LFR benchmark graphs [20] was made.

First, the three basic characteristics were studied: average path length, clustering coefficient, and degree distribution of generated networks. Figure 2a shows that average path length grows logarithmically as a function of network size (N). However, average path length of network is directly proportional to the probability of triad formation $P_t$. Figure 2b studies the impact of the probability of triad formation over average clustering coefficient of networks. Average clustering coefficient of network grows as the value of probability of triad formation ($P_t$) increases. The degree distribution of generated networks follows power law for different values of the mixing parameter (Figure 2c). This demonstrates that generated graphs possess small-world and scale-free characteristics. The consistency with original model [29] shows that proposed modification for generating ground truth communities does not affect structural characteristics of the model.

Figure 3a shows the impact of mixing parameter on geodesic distance of networks of different sizes and the number of communities as a function of mixing parameter. It also shows that geodesic distances are proportional to network sizes and the number of communities. Larger number of communities result in lesser number of nodes for each community compared to same network with lesser number of communities. Figure 3b shows impact of mixing parameter on clustering coefficient for network of size 1000, 2000 and 4000 nodes with probability of triad formation set to 0.1 and 0.5. Clustering coefficient reduces with increase in the value of mixing parameter regardless of the probability of triad formation.

It was found that geodesic distance and mixing parameter have an inverse relation and the geodesic distance decreases with reduction of the value of mixing parameter from 1 to 0. A similar impact was also observed for the value of clustering coefficient which also decreases as the value of mixing parameter is increased. This is as expected because a higher value of mixing parameter will lead to formation of edges to long distance neighbours which reduces the global geodesic distance and decreases the chances of triads in network.
Fig. 3. Impact of mixing parameter ($\mu$) on (a) average path length of graph (b) overall clustering coefficient of graph

(a) $N=\{1000, 2000, 4000\}$ & ($\varsigma$) = $\{20, 40\}$

(b) $N=\{1000, 2000, 4000\}$ & $P_t = \{0.1, 0.5\}$

Fig. 4. **Test of modularity.** This is clearly visible that modularity behaves similarly regardless of network size and size of communities ($\varsigma$) in network. The graphs generated with $P_t = 0.1$ however the similar behaviour observed for other values of $P_t$.

We use Modularity [27] to quantify the presence and quality of community structures generated in benchmark graphs by the proposed model. A good partition must have fewer edges between communities and more edges within communities. The values of modularity for different graphs vary as a function of mixing parameter. As visible in Figure 4, the quality of modular structure decreases for increasing values of mixing parameters. Results for network of size 2000 and 4000 were plotted but similar behaviour for all graphs were observed. The impact of this behaviour is indifferent to the community size which is also visible in Figure 4.

Figure 5 shows the values for four good-
Fig. 5. Goodness of community metrics with triad formation probability ($P_t$)=0.1 and Number of communities($N_0$)=20. Y-axis represents the value of specific goodness metric whereas x-axis represents the rank of community in network for that goodness metric. Each line represents behaviour of communities in increasing order for a network generated for specific value of a mixing parameter.

ness of community metrics for different values of mixing parameter. An increasing line shows that network has communities which better fit to the respective definition of community. However, it is visible that as the value of mixing parameter increases the line converges quickly which shows that communities in network do not fit for the respective definition. Similar results were observed for different sizes of network which indicates that structurally different communities can be generated in a network by tuning the value of mixing parameter.

The performance of eight community detection algorithms on graphs generated by the proposed model and LFR benchmarks are compared. The Normalized Mutual Information (NMI) was calculated to quantify the similarity between generated communities and the ground truth communities. Figure 6 shows the average for all instances of respective benchmarks for different sizes. It is already established that community detection algorithms tend to perform poorly for graphs generated with higher values of mixing parameter [21] and is supported by the observations in this result. However, it is clearly visible that graphs generated by LFR benchmarks are more sensitive than graphs generated by the proposed model for mixing parameter. It indicates that overall community detection algorithms do not behave similarly for both classes of benchmarks.

Figure 7 studies individual performance of the community detection algorithms. Each graph shows the result of one algorithm.
whereas dotted line shows the result on graphs generated by LFR benchmark and the solid line shows the results on graphs generated by the proposed model. It can be observed that all algorithms do not behave similarly for both classes of benchmarks. One can observe that Louvain, Greedy, Spinglass, Walktrap and Label Propagation behave similarly for both classes of benchmarks. As we discussed above, graphs generated by LFR benchmark are more sensitive to mixing parameter for these algorithms. Results for Infomap show similar behaviour but insensitivity to mixing parameter is clearly visible. However, the behaviour of VOS and MCL is quite different and contrary to other algorithms for graphs generated by LFR benchmark.

6 Conclusion

In this paper, a new model is proposed to generate benchmark graphs for community detection algorithms based on evolution dynamics and microscopic rules such as the preferential attachment and triadic closure. The proposed model can generate scale-free and small-world graphs with ground truth communities. The performance of eight different community detection algorithms were studied and compared with the state of the art LFR benchmark in order to study whether community detection algorithms behave similarly on graphs of similar structure but generated with different microscopic rules. It was learned that LFR benchmark is more sensitive to mixing parameter than the proposed model and all community detection algorithms do no behave similarly for both benchmarks.

One may object that, we did not investigate reasons behind the different behaviour of community detection algorithms on both benchmarks. We consider this as one of the potential future work. For this, we believe that current metrics available to compare different networks need to be revisited. There are numerous microscopic rules available in literature. As part of the future work, we also aim to study the behaviour of community detection algorithms
Fig. 7. Performance of eight community detection algorithms on two different class of benchmarks. Each plot represents one community detection algorithm for which results are averaged over all instances. Solid lines shows results on graphs generated by LFR benchmark whereas dotted line shows the results for graphs generated by BTR benchmark.

algorithms against different microscopic rules available in literature. The comparative study of quality of communities generated by benchmark graphs is another area which we intend to explore in the future.

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