Asymptotic Properties of the ABCD Graph Benchmark with Community Structure

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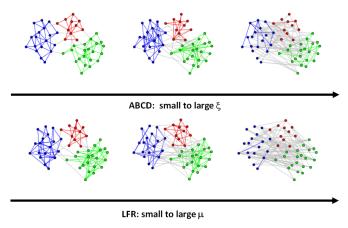
NetSci 2022, July 2022

Artificial Benchmark for Community Detection model

- power law node degree and community size distributions
 parametrized via: (min, max, exponent)
- union of k + 1 random graphs: k community subgraphs and one background graph (all nodes)
- parameter $\xi \in [0, 1]$ controls the fraction of edges that are between communities
- graphs: configuration or Chung-Lu model
- similar properties as the **LFR** benchmark
- fast Julia code and multithreaded fork: github.com/bkamins/ABCDGraphGenerator.jl github.com/tolcz/ABCDeGraphGenerator.jl

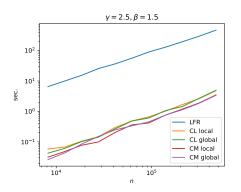
Some advantages are:

- natural interpretation of the mixing parameter ξ
 - "dimmer" from pure communities to random graph



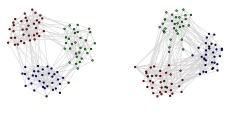
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- natural interpretation of the mixing parameter ξ
 - "dimmer" from pure communities to random graph
- better scalability than LFR
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- its simplicity, which allows for theoretical analysis



ABCD graphs with $\xi = 0.2$ and $\xi = 0.4$

The node degrees in **ABCD** are generated randomly following the (truncated) *power-law distribution* $\mathcal{P}(\gamma, \delta, \zeta)$ with exponent $\gamma \in (2,3)$, minimum value δ , and maximum value $D = n^{\zeta}$ where $\zeta \in (0,1)$.

If $X \in \mathcal{P}(\gamma, \delta, \zeta)$, then for any $k \in \{\delta, \delta + 1, \dots, D\}$,

$$q_{k} = \Pr(X = k) = \frac{\int_{k}^{k+1} x^{-\gamma} dx}{\int_{\delta}^{D+1} x^{-\gamma} dx}$$
$$= (1 + \mathcal{O}(n^{-\zeta(\gamma - 1)}) + \mathcal{O}(k^{-1})) k^{-\gamma} (\gamma - 1) \delta^{\gamma - 1}.$$

Two related lemmas:

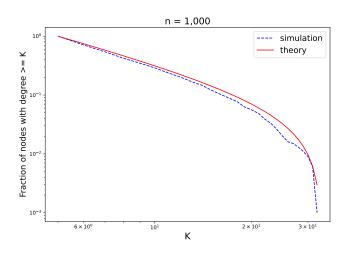
- an upper bound for the maximum degree; in particular we can assume: $\zeta \in (0, 1/(\gamma 1)]$
- the degree distribution is well concentrated around the expectation

We also show the following corollary:

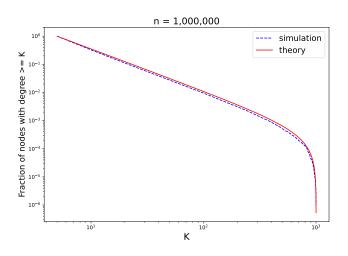
The volume of all nodes in an ABCD graph is w.e.p.1 equal to

$$vol(V) = (1 + O((\log n)^{-1})) dn$$
, where $d := \sum_{k=\delta}^{D} kq_k$

with probability at least $1 - \exp(-\Omega((\log n)^2))$ where $f(n) = \Omega(g(n))$ if $g(n) = \mathcal{O}(f(n))$



Complement of cumulative degree distribution for graphs with $\mathcal{P}(2.5, 5, 1/2), n = 1,000.$



Complement of cumulative degree distribution for graph with $\mathcal{P}(2.5, 5, 1/2), n = 1,000,000.$

Community sizes in **ABCD** are generated randomly following the (truncated) *power-law distribution* $\mathcal{P}(\beta, s, \tau)$ with exponent $\beta \in (1, 2)$, minimum value s, and maximum value $S = n^{\tau}$ with $\tau \in (\zeta, 1)$.

If $X \in \mathcal{P}(\beta, s, \tau)$, then for any $k \in \{s, s+1, \dots, S\}$,

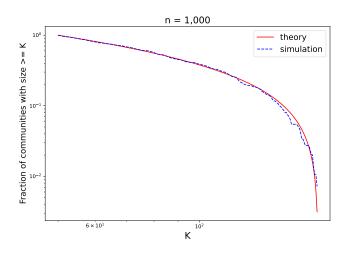
$$p_{k} = \Pr(X = k) = \frac{\int_{k}^{k+1} x^{-\beta} dx}{\int_{s}^{s+1} x^{-\beta} dx}$$
$$= (1 + \mathcal{O}(n^{-\tau(\beta-1)}) + \mathcal{O}(k^{-1})) k^{-\beta} (\beta - 1) s^{\beta-1}$$

Lemma: w.e.p. the number of communities is equal to

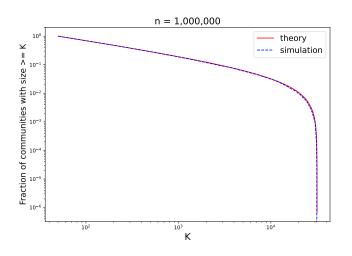
$$\ell(n) = (1 + \mathcal{O}((\log n)^{-1})) \hat{c} n^{1-\tau(2-\beta)},$$

where

$$\hat{c} = \frac{2-\beta}{(\beta-1)s^{\beta-1}}.$$



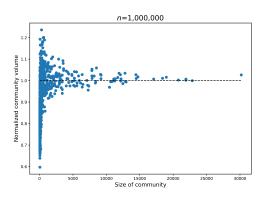
Complement of cumulative community size distribution for graph with $\mathcal{P}(1.5, 50, 3/4)$, n = 1,000.



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We can also compare the **volume** of each community with the theoretical value. As expected, larger communities show good concentration but small ones deviate from the expectation.



For a graph G = (V, E) and a partition $\mathbf{A} = \{A_1, A_2, \dots, A_\ell\}$ of V, the *modularity function* is:

$$q(\mathbf{A}) = \sum_{A_i \in \mathbf{A}} \frac{e(A_i)}{|E|} - \sum_{A_i \in \mathbf{A}} \left(\frac{\operatorname{vol}(A_i)}{\operatorname{vol}(V)}\right)^2$$

where $e(A) = |\{uv \in E : u, v \in A\}|$ is the *edge contribution*; $vol(A) = \sum_{v \in A} deg(v)$ is the *volume* of set A, and the second term is the expected value of the first under the Chung-Lu random null model.

We now investigate the modularity function for the **ABCD** model A.

We use notation $q^*(A)$ for the maximum modularity.

Theorem

Let $\mathbf{C} = \{C_1, C_2, \dots, C_\ell\}$ be the ground-truth partition of the set of nodes of \mathcal{A} . Then, w.e.p.

$$q^*(A) \ge q(\mathbf{C}) = (1 + \mathcal{O}((\log n)^{-(\gamma-2)}))(1-\xi).$$

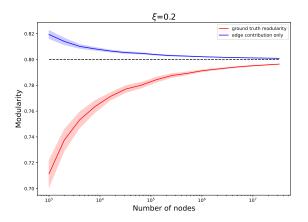


Figure: Modularity $q(\mathbf{C})$ of the ground-truth partition (red) and the corresponding edge contribution (blue) for 30 independently generated graphs. The dashed line is the asymptotic prediction; $\xi=0.2$ and other parameters as before.

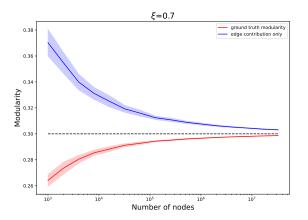


Figure: Modularity $q(\mathbf{C})$ of the ground-truth partition (red) and the corresponding edge contribution (blue) for 30 independently generated graphs. The dashed line is the asymptotic prediction; $\xi=0.7$ and other parameters as before.

We also have results comparing the **maximum** modularity $q^*(A)$ and the modularity of the ground truth partition $q(\mathbf{C})$.

For **noisy** graphs (large ξ), we show then we can find a partition with larger modularity than the ground-truth partition!

For **small values** of ξ , we show that $w.h.p.^2$ $q^*(\mathcal{A}) \sim q(\mathbf{C}) \sim 1 - \xi$, provided δ is large enough. We also show that this is not true when $\delta = 1$.





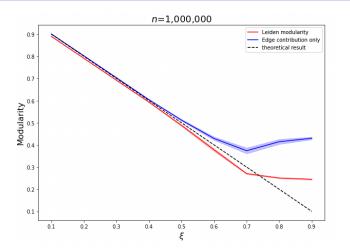


Figure: The modularity $q(\mathbf{C})$ obtained with Leiden (red) and the corresponding edge contribution (blue) for 30 independently generated graphs. The dashed line corresponds to the asymptotic prediction for the ground-truth. Same parameters as before.

References

ABCD benchmark:

- Artificial benchmark for community detection (ABCD) Fast random graph model with community structure, Network Science, 1-26 (2021)
- Properties and Performance of the ABCDe Random Graph Model with Community Structure, arXiv:2203.14899 (2022)
- github.com/bkamins/ABCDGraphGenerator.jl
- github.com/tolcz/ABCDeGraphGenerator.jl

Pre-print for this work:

 Modularity of the ABCD random graph model with community structure, arXiv:2203.01480 (2022)

In the works:

- ABCD with outliers
- Hypergraph-ABCD

