Scalable Community Detection Benchmark Generation

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Motivation

Better evaluate community detection algorithms processing O(Billion)-sized graphs on HPC resources

- Small-scale state-of-the-art: "LFR"
  - Lancichinetti, Fortunato, Radicchi, 2008
  - With >1600 citations, this is a de facto standard
  - Generates ground truth to test against
  - Has a tunable parameter for community coherence: μ
  - Limited scalability: best implementation takes ~17hrs to generate O(1B) edges (Hamann et al., 2017)
- Large-scale state-of-the-art
  - Without a reliable ground truth, parallel algorithms test with modularity or similar measures
  - This approach is flawed in several ways

Goal: *evaluate at HPC scale against ground truth*

Overview

Primary results of this work:

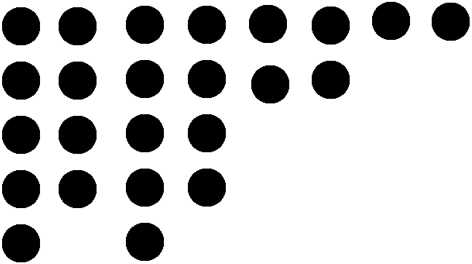
- We develop a novel method for generating large-scale graphs with a tunable ground truth community structure
- We utilize the scalable BTER generator (Kolda et al., 2014) as a core step
- Our approach generates large-scale community benchmarking graphs at a rate of 1B edge/minute on KNL
  – **Orders-of-magnitude faster than state-of-the-art**

BTER

Block Two-level Erdös-Réyni Graph Generator

- Step 0: Input degree (n_d) and clustering coefficient (c_d) distributions

d	1	2	3	4	5	6	7
n_d	9	5	4	2	2	1	1
c_d	--	0.6	0.4	0.2	0.1	0.1	0.1



BTER
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- Step 1: With ordered degree sequence, group $d+1$ vertices v of degree $d(v) >= d$ into *affinity blocks*

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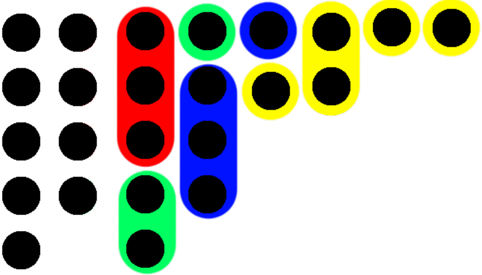

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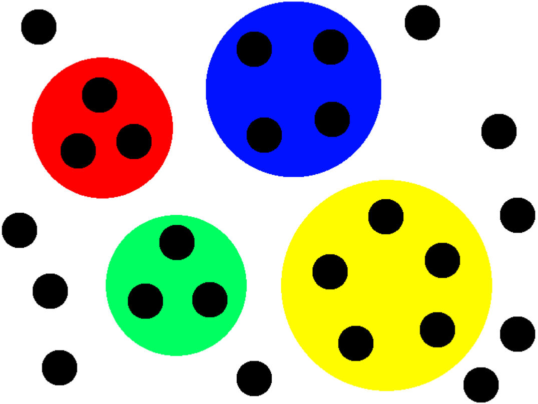

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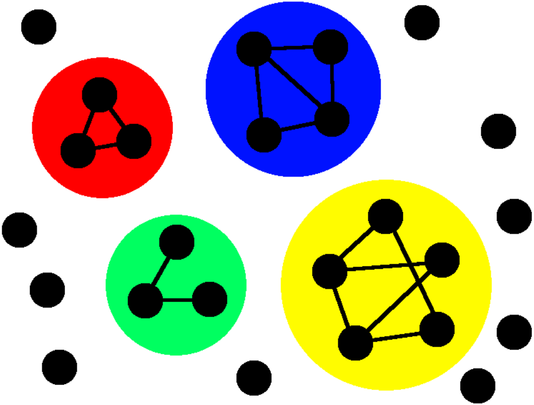

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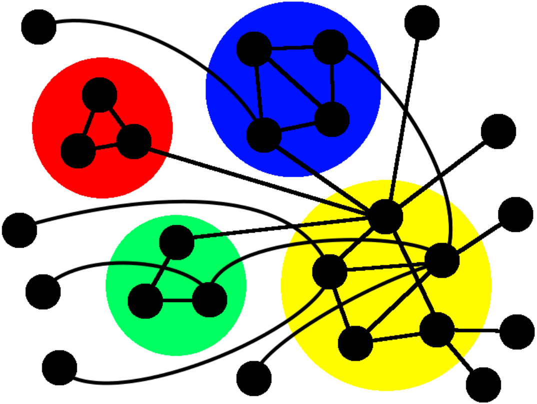
- Step 3: Create inter-block edges via Chung-Lu process



Our Implementation - For Community Detection

wBTER – wrapped BTER

How we wrap the baseline BTER process for generating graphs for community detection benchmarking:

- Treat affinity blocks as ground truth communities
- We have a *native* μ_n, based on ratio of inter- to intra-block edges generated from the original distributions
- Can shift μ_n to some target goal μ_g via a Linear Program solve (to be described) – we use Pyomo and CBC
- Our BTER implementation: fully-parallelized in shared-memory with OpenMP/C++

Linear Program

Shifting the native μ of a graph's CC distribution

Minimally shift the input clustering coefficient (CC) distribution such that the output graph has a desired goal μ_g considering both definitions:

$$\mu_g = \frac{1}{N}\sum_d \frac{d_{inter}}{d} \quad \mu_g = \frac{1}{2M}\sum_d n_d d_{inter}$$

$$\begin{aligned}
\text{minimize} \quad & \sum_d \quad |\hat{p}_d - p_d| \\
\text{subject to} \quad & \sum_d \quad n_d\hat{p}_d = N(1-\mu_g) \\
& \sum_d \quad d n_d \hat{p}_d = 2M(1-\mu_g) \\
& \qquad 0 \le \hat{p}_d \le 1 \\
\text{output} \quad & \hat{c}_d = \hat{p}_d^3
\end{aligned}$$

- p_d is $G(n,p)$ probabilities per degree from CC distribution c_d, $p_d = \sqrt[3]{c_d}$
- $\hat{p}_d$ is output probabilities to get new CC distribution $\hat{c}_d$, $\hat{c}_d = \hat{p}_d^3$
- n_d is degree distribution, n vertices of d degree
- d_{inter} is expected number of inter-community edges for vertex of degree d
- N is number of vertices in graph, M is number of edges

Experimental Setup
Test system and test graphs

Test System: *Bowman* at Sandia Labs – each node has a KNL with 68 cores, 96 GB DDR, and 16 GB MCDRAM

Test Graphs:

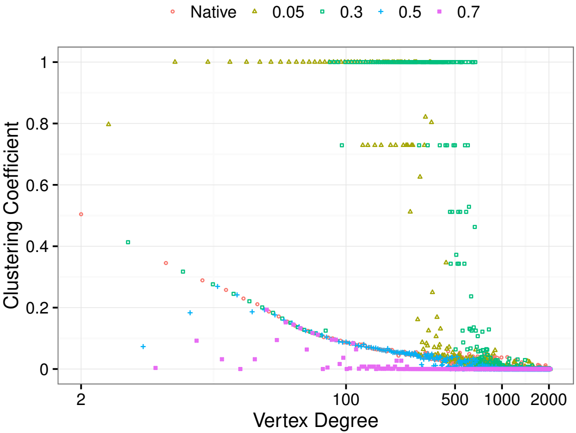
Network	n	m	$davg$	$dmax$	$\tilde{D}$
LJ-fp	4.2 M	27 M	18	20 K	18
uk-2002	18 M	261 M	28	195 K	28
Wikilinks	26 M	332 M	23	39 K	170
RMAT_26	67 M	1.1 B	16	6.7 K	8
Friendster	66 M	1.8 B	27	5.2 K	34

Graphs are from the SNAP, Koblenz, and LAW databases. LiveJournal-fp is a parsed version of LiveJournal from SNAP.

Shifting Distribution

How the CC distribution shifts for varying μ

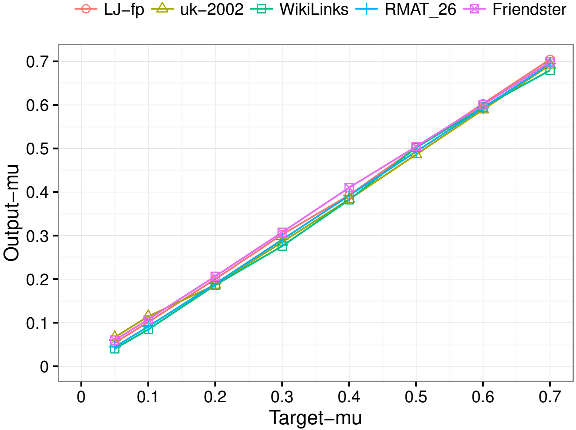
- Only every 5$^{\text{th}}$ value plotted for better visualization
- Generally, distribution is most "accurate" near *native* μ
- Better *smoothing* of distribution via LP constraints is future work



Hitting Target Mu

Accuracy of LP for generating desired μ

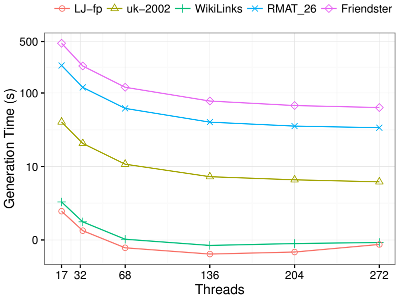
- Generation accuracy is comparable to LFR
- Less than 5% error in most instances
- Error is greatest at lower μ targets

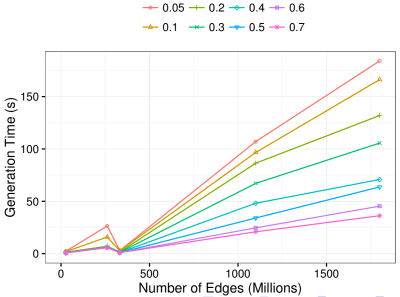


Generation time vs. target μ

(Left) Time vs. μ – (Right) Time vs. graph scale

- Strong scaling generally good up to 2 threads/core
- Time decreases with increasing μ, due to *coupon collectors* edge generation scaling - higher CC requires more attempts for each edge
- Generation time a function of scale and complexity (max degree)
- Average ~2 minutes for 1.8B unique edges
  - Original BTER code: ~4 min. for 1.2B edges on 32 node Hadoop cluster
  - Fastest LFR implementation: 17 hours for 1B edges in shared-memory





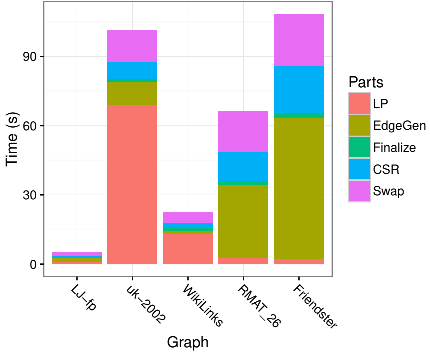
A Note on BTER Assortativity

- An issue with our approach so far is the degree homogeneity of communities
- We propose the following addition:
  - Consider intra-comm edge count of each vertex
  - Permute community assignments of all vertices with same count
  - **Observation**: won't affect μ, de-homogenizes communities in terms of degree
- This approach might also be applied to baseline BTER generation

Timing Breakdown

Full wBTER approach with community permutation, $\mu = 0.5$

- Time costs of major wBTER steps with community assignment permutation
- **Work Complexity**: $d = D_{max}, n = |V|, m = |E|$
  - LP: expected to scale as $O(d \log d)$
  - EdgeGen: $O(m \log d)$
  - Finalize: $O(n + m)$
  - CSR: $O(n + m)$
  - Swap: $O(n \log n + m)$



LP: linear program
EdgeGen: primary BTER phase
Finalize: remove 0-degree vertices & cleanup
CSR: create graph representation
Swap: community degree permutation

Conclusions
and future work

- We shift a graph's CCD to fit a μ generated by BTER
- Our approach can output graphs for community detection order-of-magnitudes faster than commonly-used generators, e.g., LFR
- Our approach can output graphs with more realistic degree and CC distributions than commonly-used generators
- Future Work:
  - Better develop LP to reduce noise in output CC distribution
  - Shift graph scale – i.e., output equivalent distributions for a graph with $2\times$, $\frac{1}{2}\times$ original scale
  - Develop generation methods for hierarchical communities

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