A Parallel LFR-like Benchmark for Evaluating Community Detection Algorithms

George M. Slota and Jack Garbus

Rensselaer Polytechnic Institute

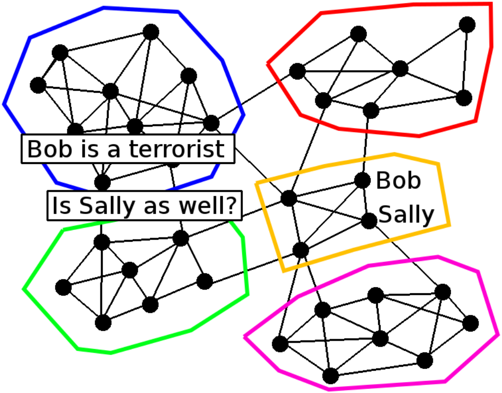
ParSocial 2020

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525.

What is community detection?

Community Detection: Basic problem

- We have some real-world interaction network (e.g., Facebook)
- Community detection: identifying *clusters* within the network
- Why: communities are often homogeneous (like-attracts-like) so we can often infer information about community members.



Community Detection Algorithms: Evaluation

How do we evaluate algorithm solution quality?

Given some community detection algorithm, how can we determine the quality of its output?

- **Ideally:** Evaluate on real-world datasets with "known" communities
  – Very few such datasets exists, none at HPC/real-world social network scale
- **Measure:** Calculate some global measurement such as modularity (how well-clustered is the solution)
- **Compare:** Generate synthetic networks with an "ground-truth" set of communities
  – This is the approach of the well-known *LFR Benchmark*
  – This work focuses on generating large-scale LFR-like test benchmarks
  – For various reasons, this approach is **highly preferred** to modularity evaluation

Current State-of-the-Art: LFR

For benchmark graph generation with engineered solutions

"Lancichinetti–Fortunato–Radicchi" (LFR)[1]:

- With >1600 citations, this is a de facto standard
- Generates approximate solution to test against
  – **Uses tunable parameter for community coherence:** μ
- Limited scalability: best implementation takes ~17hrs to generate ~10B edges[2]
  – Original code takes hours for million+ edge graphs

Our recent work: Adapted-BTER[3]

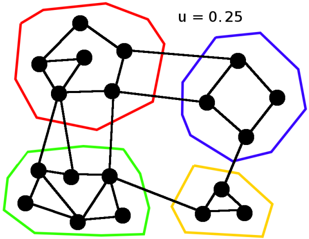
- Generates graphs that match an input degree distribution, but not a community size distribution
- However: scales to trillion-edge graph generation (and takes only minutes!)

[1] [Lancichinetti et al., 2008]
[2] [Hamann et al., 2018]
[3] [Slota et al., 2019]

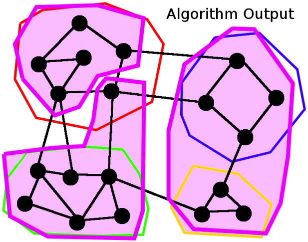
LFR Benchmark Graph Generation

Community Detection Algorithms: Evaluating with a ground truth

- Generate a synthetic network with some set of "communities"
- Include a *mixing parameter* – μ – that controls the ratio of inter- to intra-community edges: $\mu \approx \frac{\text{inter-comm. edges}}{\text{total edges}}$
  – Effectively, this determines how well-defined the communities are
- Evaluate how well an algorithm's output matches the defined solution
  – Commonly utilize Normalized Mutual Information (NMI)
  – Compare how well algorithms perform as you increase edge mixing via μ



$\rightarrow$



Scalable Parallel Methods for LFR-like Generation

Benchmark graph generation for community detection

We implement two hierarchical parallel approaches:
– Shared-Memory `OpenMP`: Configuration Model Chung-Lu (CMCL)
– Distributed-Memory `MPI+OpenMP`: Two-level Chung-Lu (TLCL)

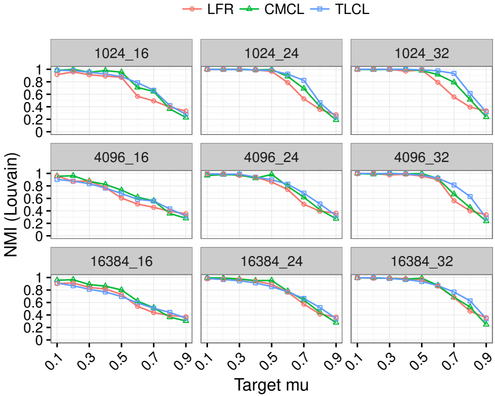
Both follow the same general algorithmic approach:

- Phase 1: Initialize input distributions
  – Power-law distributions for community sizes and the degree distribution; can be generated in parallel
- Phase 2: Parallel assignment of vertices to communities
- Phase 3: Parallel internal edge generation
  – Use configuration model or Chung-Lu to generate intra-community edges
- Phase 4: External edge generation
  – Use Chung-Lu to generate inter-community edges

In-practice Benchmark Performance

Running on generated graphs with the Louvain Algorithm

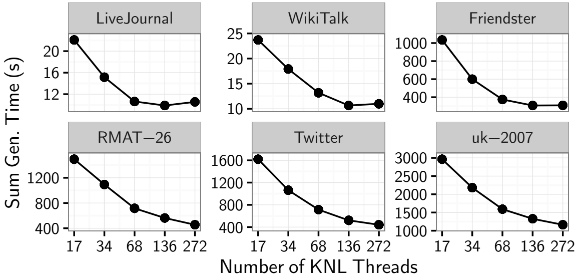
- We run the Louvain Algorithm [Blondel et al., 2008] on networks generated with CMCL, TLCL, and LFR and evaluate NMI
- Parameters: Num Vertices = 1024, 4096, 16384; Avg. Degree = 16, 24, 32; $\mu = 0.1 \ldots 0.9$
- We note near-identical outputs from all three benchmarks



Strong Scaling of CMCL

We run strong scaling experiments with CMCL on single Intel Knight's Landing node (17-272 threads)

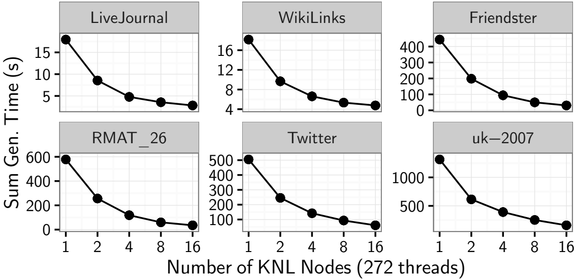
- We run using degree distributions from well-known test instances
- Times given are the sum time for generating 9 benchmark graphs with $\mu = 0.1 \ldots 0.9$
- It takes about 15 minutes in total to generate a full set of instances with over 3 billion edges each from the uk-2007 distribution



Strong Scaling of TLCL

We run strong scaling experiments with TLCL on 16 Intel Knight's Landing nodes (272 threads each)

- We run using the same instances and setup as the CMCL experiments
- We have on average over $10\times$ speedup vs. shared-memory
- All 9 instances for the 3 billion edge uk-2007 input takes in total only 1.5 minutes to generate



Conclusions and thanks!

Major takeaways:

- We develop a scalable method for generating LFR-like community detection algorithm benchmarking graphs
- This generates test instances at HPC-scale – orders-of-magnitude larger than the serial LFR code and order-of-magnitude faster than recent parallel LFR codes
- Code to be released to `https://github.com/HPCGraphAnalysis/SAGE` pending copyright approvals

Thank you! Contact below with any questions.

slotag@rpi.edu   www.gmslota.com

Bibliography I

Vincent D Blondel, Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10):P10008, 2008. URL http://stacks.iop.org/1742-5468/2008/i=10/a=P10008.

Michael Hamann, Ulrich Meyer, Manuel Penschuck, Hung Tran, and Dorothea Wagner. I/o-efficient generation of massive graphs following the LFR benchmark. *J. Exp. Algorithmics*, 23(1):2.5:1–2.5:33, August 2018. ISSN 1084-6654. doi: 10.1145/3230743. URL http://doi.acm.org/10.1145/3230743.

Andrea Lancichinetti, Santo Fortunato, and Filippo Radicchi. Benchmark graphs for testing community detection algorithms. *Physical Review E*, 78(4):1–5, October 2008. ISSN 1539-3755. doi: 10.1103/PhysRevE.78.046110.

G. M. Slota, J. Berry, S. D. Hammond, S. Olivier, C. Phillips, and S. Rajamanickam. Scalable generation of graphs for benchmarking hpc community-detection algorithms. In *SC*, 2019.