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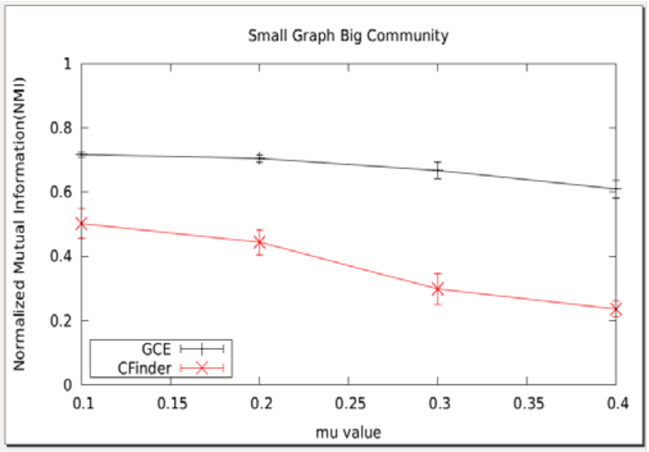

Figure 3 (b): Small Graph and Big Community

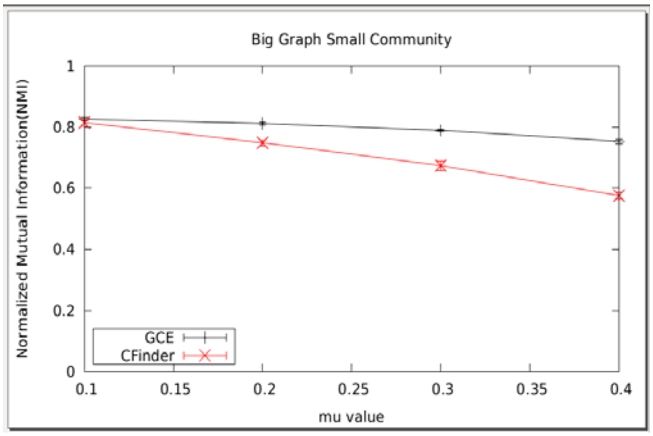

Figure 3 (c): Big Graph and Small Community

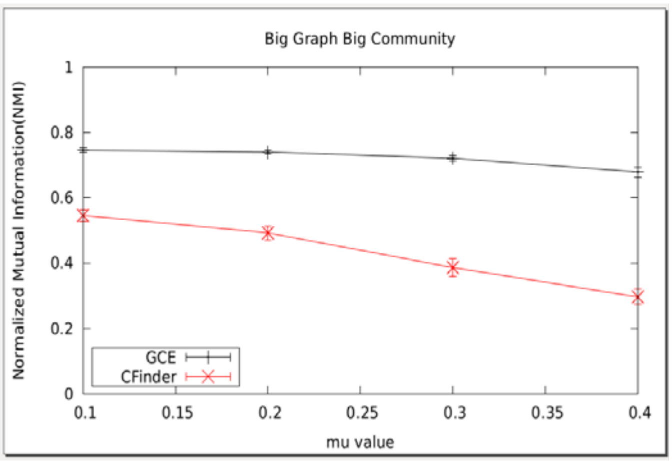

Figure 3 (d): Big Graph and Big Community

CASE	LFR		ELFR	
	GCE	CFinder	GCE	CFinder
Small Graph and Small	0.7033	0.6256	0.7569	0.6315
Small Graph and Big	0.6306	0.3651	0.6747	0.3699
Big Graph and Small	0.7815	0.6990	0.7958	0.7037
Big Graph and Big	0.7051	0.4262	0.7213	0.4301

6.3 Performance of Extended LFR benchmark against Normal LFR benchmark

Table: Comparing NMI values of GCE and CFinder algorithms of LFR and ELFR. For a small graph with smaller communities, we can orderly observe that extended LFR benchmark is 5% better than the normal LFR benchmark in GCE case and only 1% in case of CFinder. Same in the case with small graph with big communities by 3% and 1%. For a big graph with small communities their difference is not very high this just 1% in both the algorithms. In the last case, such as big graph with big communities also the difference is just 2% and 1%.

7. Conclusion & Future Work

We conclude that the tests were conducted on different sets of benchmark networks to compare the above overlapping community detection algorithms. In our observation, we found that GCE is performing well. We have also observed that extended LFR benchmark performance is better than normal LFR benchmark. However these set of benchmarks only takes care of topological properties of networks. Nevertheless, most of the real networks come with attributes. As the community structure must relate to these attributes, in future we would like to implement an LFR benchmark while taking care of topological properties as well as node attributes.

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