Group extraction for real-world networks Lovro Šubelj¹, Neli Blagus & Marko Bajec

Background

Complex real-world networks contain characteristic groups of nodes with common linking pattern like densely linked communities [1]. These were the focus of most recent work and have diverse applications. However, many real-world networks also contain other groups of nodes that can be overlapping and other, whereas some parts of the networks reveal no significant groups.

Group **formalism**



Let W be the group criterion, L the number of links and μ the (harmonic) mean size.

$$W(S,T) = \mu(S,T) \left(1 - \mu(S,T)\right) \left(\frac{L(S,T)}{|S||T|} - \frac{L(S,T^{C})}{|S||T^{C}|}\right)$$

W is a local asymmetric criterion that favors the links between S and T, and penalizes for th links between S and T^C. (Note, however, that W disregards the links with both endpoints in S^{C} For S = T, W is consistent with a wide class of other models (e.g., *stochastic blockmodel*). [2

Group extraction

A sequential extraction [2] of groups that can be overlapping, nested etc.

- (1) Find S and T that optimize criterion W (e.g., tabu search).
- (2) Extract only the explained links between S and T (and isolated nodes).
- (3) **Repeat** until *W* is larger than expected in a random graph (by simulation).

Contributions

1. A simple formalism and criterion for general groups of nodes.

- 2. An adequate extraction procedure for statistically significant groups.
- 3. Characterization of the group structure of different real-world networks.

University of Ljubljana, Faculty of Computer and Information Science, Slovenia

What are characteristic groups of nodes in real-world networks? Network (type) dependent. What portion of network links is explained by the group structure? Between 60% and 90%. What portion of network nodes is included in the group structure? More than 50%.

Groups in **real-world networks**

	Network	Nodes	Links		Group		Community	Core	Mixture	Module	Background
2				#	S	au	% Links (% nodes)				
.)	Author collaborat. $[3]$	1589	2742	160	5.6	0.94	71%~(47%)	$0\% \; (0\%)$	6%~(5%)	1%~(1%)	22% (47%)
	American football [1]	115	613	13	8.6	0.88	${f 59\%}~({f 83\%})$	9%~(11%)	3%~(7%)	0% (0%)	29%~(98%)
2]	Lucene search engine	1657	6808	123	12.1	0.55	19%~(25%)	1%~(2%)	30 % (24%)	${\bf 38\%}~({\bf 34\%})$	11%~(49%)
	Colt computing [4]	227	963	15	10.3	0.41	7%~(11%)	5%~(6%)	69 % (49 %)	4%~(6%)	15%~(64%)
	Word adjacency [3]	112	425	4	11.2	0.28	$0\% \ (0\%)$	0%~(0%)	${f 34\%}$ $({f 33\%})$	25%~(15%)	41%~(99%)
	Internet overlay $[5]$	767	1857	33	10.6	0.08	0%~(1%)	12%~(4%)	13%~(7%)	$\mathbf{34\%}~(\mathbf{35\%})$	41%~(80%)
	Southern women $[6]$	32	89	2	4.3	0.00	$0\% \ (0\%)$	0%~(0%)	$0\% \ (0\%)$	80 % (41%)	20% (47%)

All extracted groups are statistically significant at 1% level.

References

[1] Girvan, M. & Newman, M.E.J.: Community structure in social and biological networks. P. Natl. Acad. Sci. USA 99(12), 7821–7826 (2002). [2] Zhao, Y., Levina, E., & Zhu, J.: Community extraction for social networks. P. Natl. Acad. Sci. USA 108(18), 7321-7326 (2011). [3] Newman, M. E. J.: Finding community structure in networks using the eigenvectors of matrices. Phys. Rev. E 74(3), 036104 (2006). [4] Šubelj, L. & Bajec, M.: Community structure of complex software systems: Analysis and applications. Physica A 390(16), 2968-2975 (2011). [5] Leskovec, J., Kleinberg, & J., Faloutsos, C.: Graphs over time: Densification laws, shrinking diameters and possible explanations. In: Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (Chicago, IL, USA, 2005), pp. 177–187. [6] Davis, A., Gardner, B.B., & Gardner, M.R.: *Deep South* (Chicago University Press, Chicago, 1941).



¹Corresponding author: lovro.subelj@fri.uni-lj.si