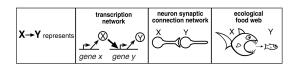
subgraphs or fragments

introduction to network analysis (ina)

Lovro Šubelj University of Ljubljana spring 2023/24

fragments definition

- small subgraphs are building blocks of networks
- subgraphs characterize local network structure



- *fragments* = *connected subgraphs* of networks [EK15]
- motifs = frequent non-induced subgraphs [MSOI+02]
- graphlets = specific induced subgraphs [PCJ04]

see mfinder and orca for implementations

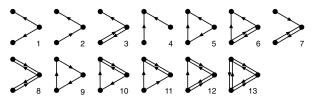
network *motifs*

introduction to network analysis (ina)

Lovro Šubelj University of Ljubljana spring 2023/24

motifs definition

- fragments characterize network-wise local structure
- motifs are frequent non-induced fragments [MSOI+02] probability of motif appearing in random graph equal or greater number of times is < 0.01</p>
- (un)directed motifs consisting of three to five/six/seven nodes



all 13 directed three-node motifs

motifs significance

- motif significance Z with normal distribution N(0,1)
 - $-\widetilde{n}_i$ is number of motifs i in random graph with variance $\widetilde{\sigma}_i^2$
 - n_i is number of motifs i in real network

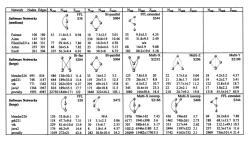
$$Z_i = \frac{n_i - \langle \widetilde{n}_i \rangle}{\widetilde{\sigma}_i}$$
 $n_i - \langle \widetilde{n}_i \rangle > 0.1 \langle \widetilde{n}_i \rangle$

— $\tilde{n}/\tilde{\sigma}$ estimated by motif preserving randomization [MSOI+02]

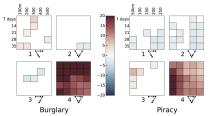
Network	Nodes	Edges	N _{real}	$N_{\rm rand} \pm {\rm SD}$	Z score	N _{real}	$N_{\rm rand} \pm {\rm SD}$	Z score	$N_{\rm real}$	N _{rand} ± SE	Z score
Neurons			V Y Y Y Z		Feed- forward loop	x y w		Bi-fan	V X M YM WZ		Bi- parallel
C. elegans†	252	509	125	90 ± 10	3.7	127	55 ± 13	5.3	227	35 ± 10	20
Food webs				X V	Three chain	μ,	' M	Bi- parallel			
			l	Y V Z		Α,	K				
Little Rock	92	984	3219	Z 3120 ± 50	2.1	7295	2220 ± 210	25			
Ythan	83	391	1182	1020 ± 30	7.2	1357	230 ± 50	23			
St. Martin	42	205	469	450 ± 10	NS	382	130 ± 20	12			
Electronic circuits (forward logic chips)			$\begin{bmatrix} \mathbf{x} \\ \mathbf{y} \\ \mathbf{y} \\ \mathbf{z} \end{bmatrix}$		Feed- forward loop	X Y W		Bi-fan	Y Z Bi- y Z para		Bi- parallel
s15850	10,383	14,240	424	2 ± 2	285	1040	1 ± 1	1200	480	2 ± 1	335
s38584	20,717	34,204	413	10 ± 3	120	1739	6 ± 2	800	711	9 ± 2	320
s38417	23,843	33,661	612	3 ± 2	400	2404	1 ± 1	2550	531	2 ± 2	340
World Wide Web			>x y y z		Feedback with two mutual dyads	$y \longleftrightarrow z$		Fully connected triad	$y \longleftrightarrow z$		Uplinked mutual dyad
nd.edu§	325,729	1.46e6	1.1e5	2e3 ± 1e2	800	6.8e6	5e4±4e2	15,000	1.2e6	1e4 ± 2e3	2 5000

motifs examples

motif Z-scores of class software networks [VS05]



motif Z-scores of spatio-temporal crime networks [DM15]



motifs *profiles*

- motif significance profile SP [MSOI+02] defined as
 - Z_i is significance of motif i in real network

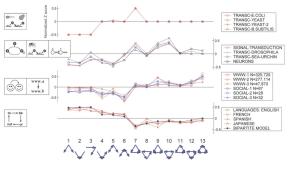
$$SP_i = \frac{Z_i}{\sqrt{\sum_i Z_i^2}}$$
 $Z_i = \frac{n_i - \langle \widetilde{n}_i \rangle}{\widetilde{\sigma}_i}$ $n_i \ge 4$

- motif abundance/ratio profile RP [MIK+04] defined as
 - A_i is abundance of motif i in real network

$$RP_i = \frac{A_i}{\sqrt{\sum_i A_i^2}}$$
 $A_i = \frac{n_i - \langle \widetilde{n}_i \rangle}{n_i + \langle \widetilde{n}_i \rangle + \epsilon_i}$ $\epsilon_i = 4$

motifs families

- directed motif significance profiles [MSOI+02]
- profiles reveal (super)families of real networks



all 13 directed three-node motifs

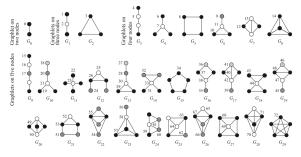
network graphlets

introduction to network analysis (ina)

Lovro Šubelj University of Ljubljana spring 2023/24

graphlets definition

- fragments characterize node-wise local structure
- graphlets are specific induced fragments [PCJ04]
- graphlet orbits are automorphisms of graphlets [Prž07]
- (un)directed graphlets consisting of three to five/... nodes



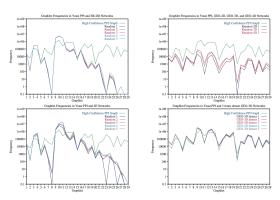
all 30 undirected two- to five-node graphlets with 73 orbits

graphlets frequency

— relative graphlet frequency F [PCJ04] defined as

- n; is number of graphlets i in real network

$$F_i = \frac{n_i}{\sum_i n_i}$$

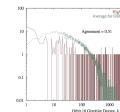


graphlet frequency in protein network and random graphs

graphlets distribution

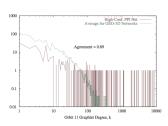
- *i-th orbit graphlet degree distribution* p_k^i [Prž07] defined as
 - $-p_k^0$ is degree distribution p_k of real network
 - $-p_k^i$ is graphlet degree distribution for i-th orbit
 - $-\widetilde{p}_{k}^{i}$ is scaled graphlet degree distribution for i-th orbit

$$\widetilde{p}_k^i \sim p_k^i/k$$



100000

 $\widetilde{p}_k^0 = p_k^0 = p_k$





graphlets agreement

- i-th orbit graphlet agreement A; [Prž07] defined as
 - $-\widetilde{p}_{k}^{i}$ is i-th orbit graphlet degree distribution of first network
 - $-\widetilde{q}_k^i$ is i-th orbit graphlet degree distribution of second network

$$A_i = 1 - \sqrt{\frac{1}{2} \sum_k \left(\log \widetilde{q}_k^i - \log \widetilde{p}_k^i \right)^2}$$

arithmetic/geometric graphlet agreement A defined as

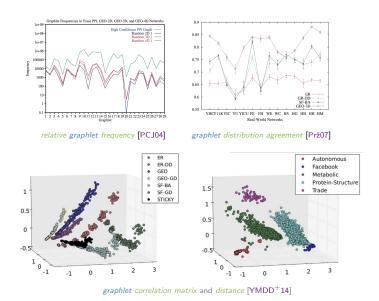
$$A = \frac{1}{73} \sum_{i} A_{i} \qquad \qquad A = \left(\prod_{i} A_{i}\right)^{\frac{1}{73}}$$

$$A = \left(\prod_{i} A_{i}\right)^{\frac{1}{73}}$$

$$A$$

arithmetic/geometric graphlet agreement of protein networks and random graphs

graphlets *measures*



fragments references



A.-L. Barabási.

Network Science.

Cambridge University Press, Cambridge, 2016.



Toby Davies and Elio Marchione.

Event networks and the identification of crime pattern motifs.

PLoS ONE, 10(11):e0143638, 2015.



Wouter de Nooy, Andrej Mrvar, and Vladimir Batagelj.

Exploratory Social Network Analysis with Pajek: Expanded and Revised Second Edition. Cambridge University Press, Cambridge, 2011.



David Easley and Jon Kleinberg.

Networks, Crowds, and Markets: Reasoning About a Highly Connected World.
Cambridge University Press. Cambridge. 2010.



Ernesto Estrada and Philip A. Knight.

A First Course in Network Theory.

Oxford University Press, 2015.



Ron Milo, Shalev Itzkovitz, Nadav Kashtan, Reuven Levitt, Shai Shen-Orr, Inbal Ayzenshtat, Michal Sheffer, and Uri Alon.

Superfamilies of evolved and designed networks.

Science, 303(5663):1538-1542, 2004.



R. Milo, S. Shen-Orr, S. Itzkovitz, N. Kashtan, D. Chklovskii, and U. Alon.

Network motifs: Simple building blocks of complex networks.

Science, 298(5594):824-827, 2002.

fragments references



Mark E. J. Newman.

Networks.

Oxford University Press, Oxford, 2nd edition, 2018.



N. Pržulj, D. G. Corneil, and I. Jurisica.

Modeling interactome: Scale-free or geometric? *Bioinformatics*, 20(18):3508–3515, 2004.



Nataša Pržulj.

Biological network comparison using graphlet degree distribution.

Bioinformatics, 23(2):e177-e183, 2007.



Sergi Valverde and Ricard V. Solé.

Network motifs in computational graphs: A case study in software architecture.

Phys. Rev. E, 72(2):026107, 2005.



Ömer Nebil Yaveroğlu, Noël Malod-Dognin, Darren Davis, Zoran Levnajić, Vuk Janjic, Rasa Karapandza, Aleksandar Stoimirovic. and Nataša Pržuli.

Revealing the hidden language of complex networks.

Sci. Rep., 4:4547, 2014.