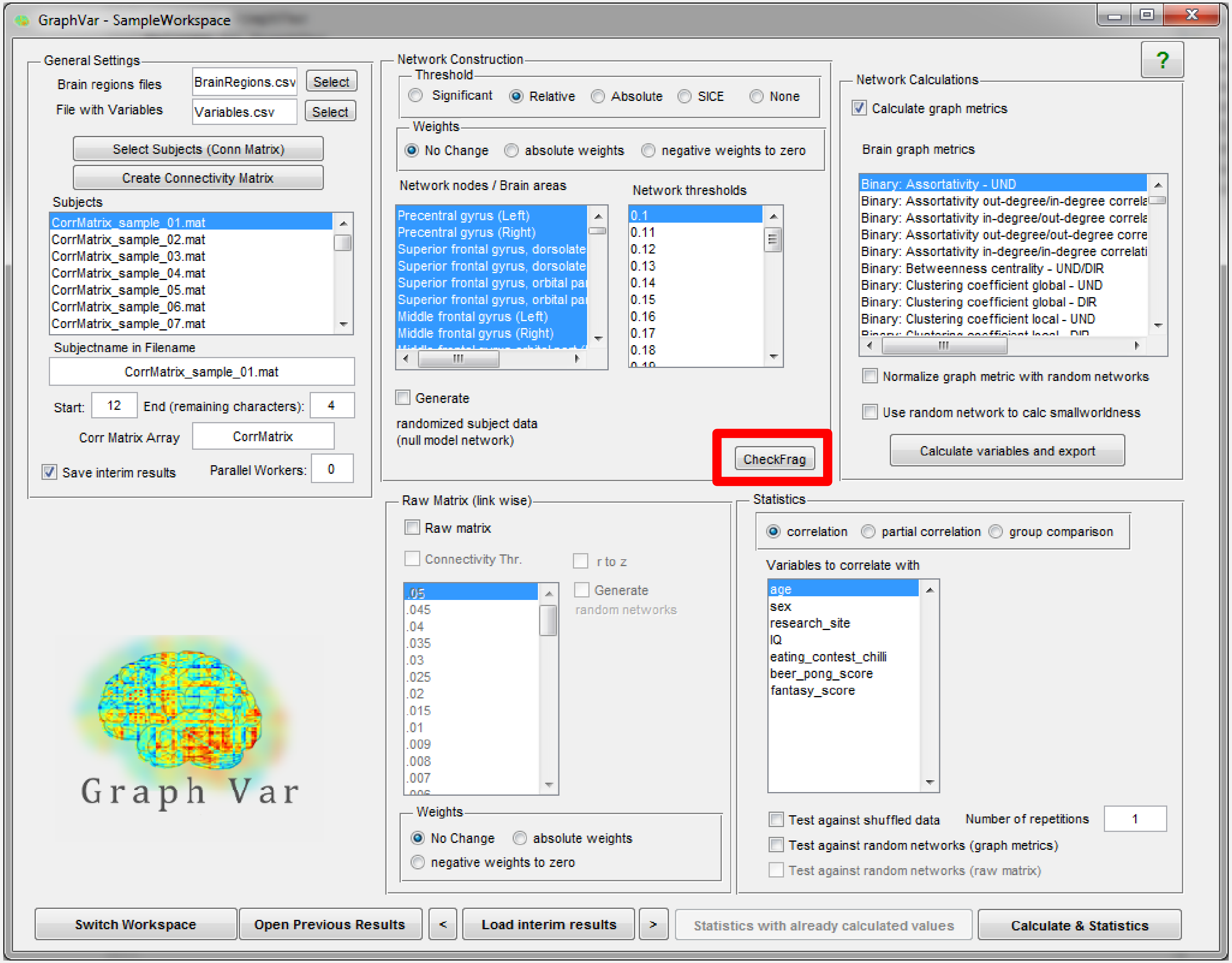
GraphVar beta 0.62 new features

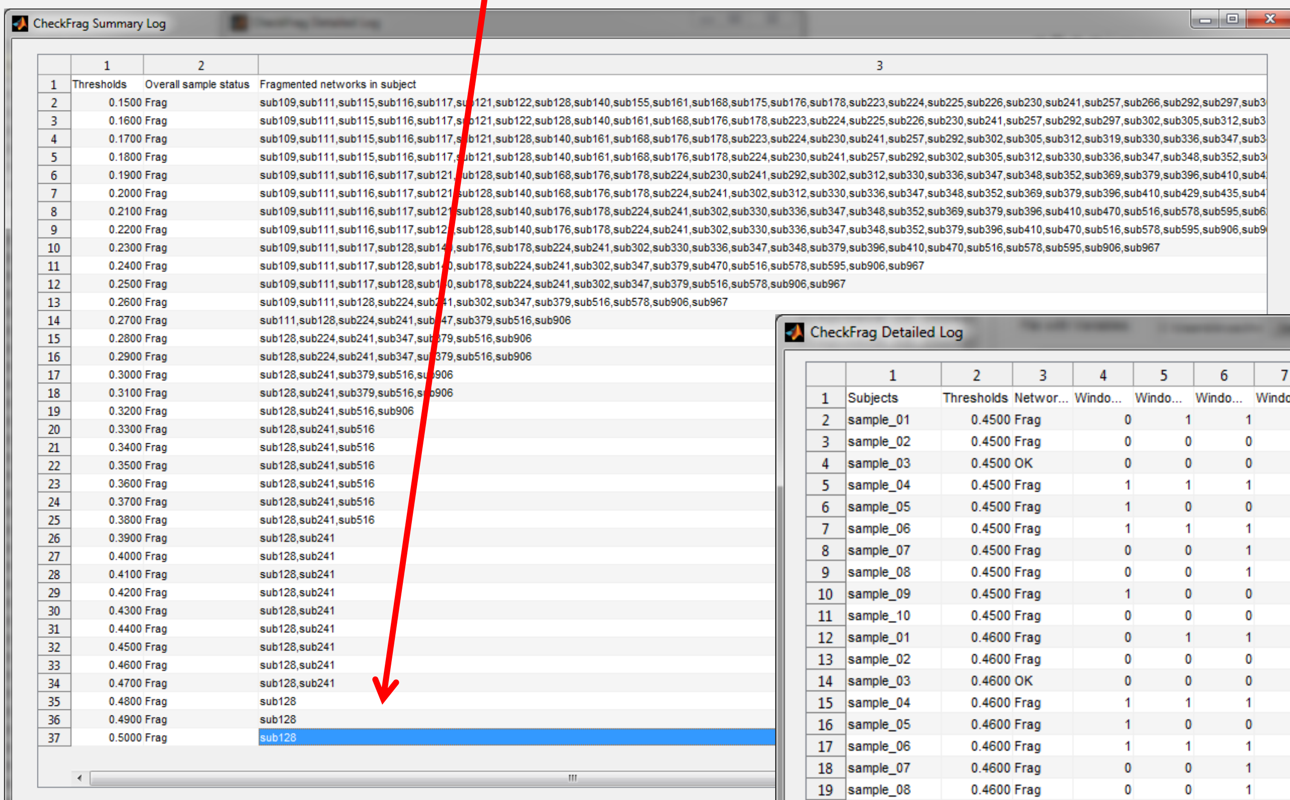


CheckFrag – check network fragmentation

CheckFrag: will check if network fragmentation (i.e. disconnected nodes) with respect to the settings in your network construction occur (saved as csv files in your result folder). This may give you a better idea of what you are looking at.

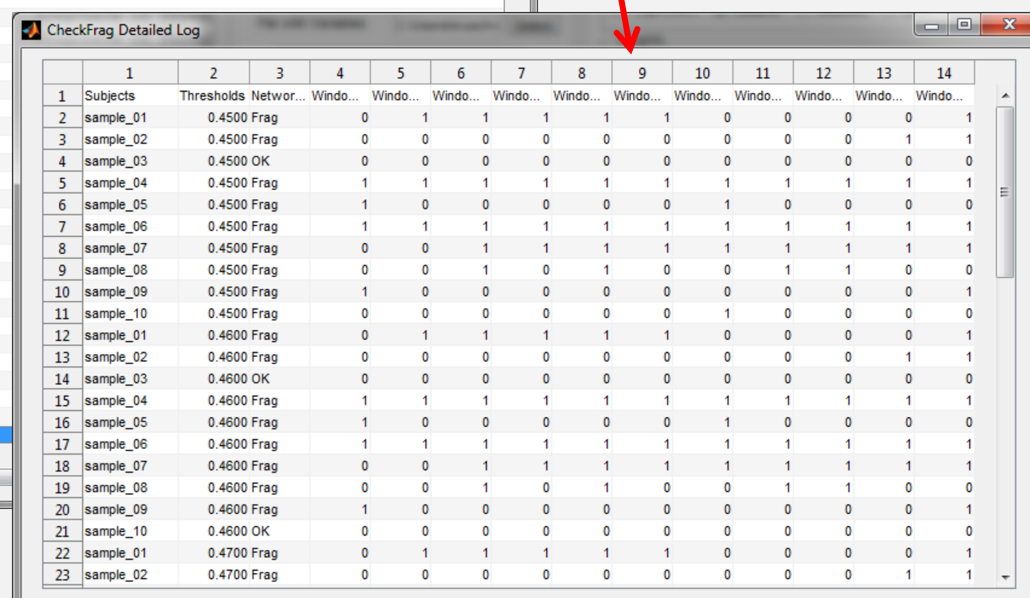
… this may be especially usefull in sliding window analyses
(if you want to make sure that all nodes are always part of the network)

… this may also be usefull in finding „strange“ subjects (e.g. bad data)



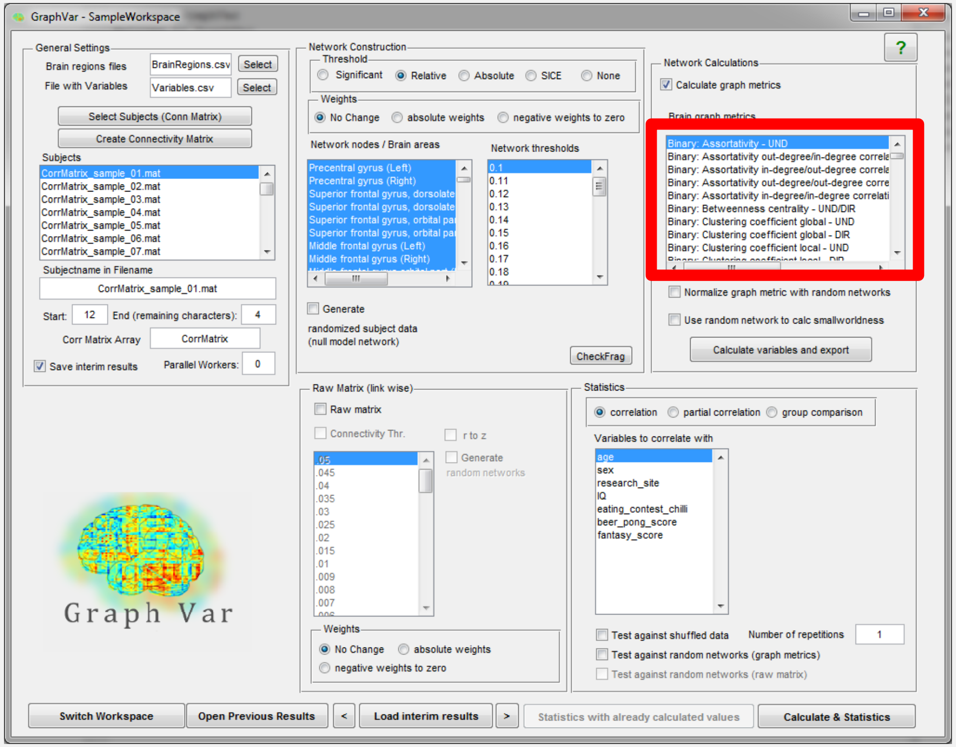
CheckFrag Summary Log

	1	2	3
1	Thresholds	Overall sample status	Fragmented networks in subject
2	0.1500	Frag	sub109,sub111,sub115,sub116,sub117,sub121,sub122,sub128,sub140,sub155,sub161,sub168,sub175,sub176,sub178,sub223,sub224,sub225,sub226,sub230,sub241,sub257,sub266,sub292,sub297,sub3
3	0.1600	Frag	sub109,sub111,sub115,sub116,sub117,sub121,sub122,sub128,sub140,sub161,sub168,sub176,sub178,sub223,sub224,sub225,sub226,sub230,sub241,sub257,sub292,sub297,sub302,sub305,sub312,sub3
4	0.1700	Frag	sub109,sub111,sub115,sub116,sub117,sub121,sub128,sub140,sub161,sub168,sub176,sub178,sub223,sub224,sub230,sub241,sub257,sub292,sub302,sub305,sub312,sub319,sub330,sub336,sub347,sub3
5	0.1800	Frag	sub109,sub111,sub115,sub116,sub117,sub121,sub128,sub140,sub161,sub168,sub176,sub178,sub224,sub230,sub241,sub257,sub292,sub302,sub305,sub312,sub330,sub336,sub347,sub348,sub352,sub3
6	0.1900	Frag	sub109,sub111,sub116,sub117,sub121,sub128,sub140,sub168,sub176,sub178,sub224,sub230,sub241,sub292,sub302,sub312,sub330,sub336,sub347,sub348,sub352,sub369,sub379,sub396,sub410,sub4
7	0.2000	Frag	sub109,sub111,sub116,sub117,sub121,sub128,sub140,sub168,sub176,sub178,sub224,sub241,sub302,sub312,sub330,sub336,sub347,sub348,sub352,sub369,sub379,sub396,sub410,sub429,sub435,sub4
8	0.2100	Frag	sub109,sub111,sub116,sub117,sub121,sub128,sub140,sub176,sub178,sub224,sub241,sub302,sub330,sub336,sub347,sub348,sub352,sub369,sub379,sub396,sub410,sub470,sub516,sub578,sub595,sub6
9	0.2200	Frag	sub109,sub111,sub116,sub117,sub121,sub128,sub140,sub176,sub178,sub224,sub241,sub302,sub330,sub336,sub347,sub348,sub352,sub379,sub396,sub410,sub470,sub516,sub578,sub595,sub906,sub9
10	0.2300	Frag	sub109,sub111,sub117,sub128,sub140,sub176,sub178,sub224,sub241,sub302,sub330,sub336,sub347,sub348,sub379,sub396,sub410,sub470,sub516,sub578,sub595,sub906,sub967
11	0.2400	Frag	sub109,sub111,sub117,sub128,sub140,sub178,sub224,sub241,sub302,sub347,sub379,sub470,sub516,sub578,sub595,sub906,sub967
12	0.2500	Frag	sub109,sub111,sub117,sub128,sub140,sub178,sub224,sub241,sub302,sub347,sub379,sub516,sub578,sub906,sub967
13	0.2600	Frag	sub109,sub111,sub128,sub224,sub241,sub302,sub347,sub379,sub516,sub578,sub906,sub967
14	0.2700	Frag	sub111,sub128,sub224,sub241,sub347,sub379,sub516,sub906
15	0.2800	Frag	sub128,sub224,sub241,sub347,sub379,sub516,sub906
16	0.2900	Frag	sub128,sub224,sub241,sub347,sub379,sub516,sub906
17	0.3000	Frag	sub128,sub241,sub379,sub516,sub906
18	0.3100	Frag	sub128,sub241,sub379,sub516,sub906
19	0.3200	Frag	sub128,sub241,sub516,sub906
20	0.3300	Frag	sub128,sub241,sub516
21	0.3400	Frag	sub128,sub241,sub516
22	0.3500	Frag	sub128,sub241,sub516
23	0.3600	Frag	sub128,sub241,sub516
24	0.3700	Frag	sub128,sub241,sub516
25	0.3800	Frag	sub128,sub241,sub516
26	0.3900	Frag	sub128,sub241
27	0.4000	Frag	sub128,sub241
28	0.4100	Frag	sub128,sub241
29	0.4200	Frag	sub128,sub241
30	0.4300	Frag	sub128,sub241
31	0.4400	Frag	sub128,sub241
32	0.4500	Frag	sub128,sub241
33	0.4600	Frag	sub128,sub241
34	0.4700	Frag	sub128,sub241
35	0.4800	Frag	sub128
36	0.4900	Frag	sub128
37	0.5000	Frag	sub128

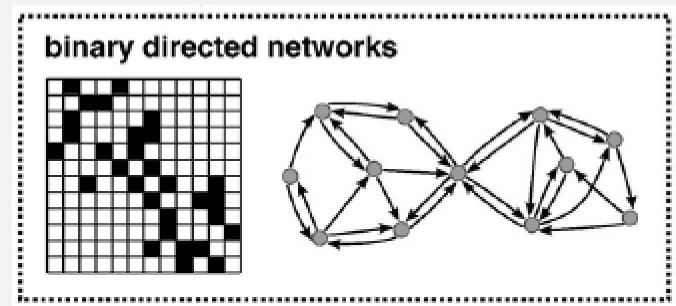


CheckFrag Detailed Log

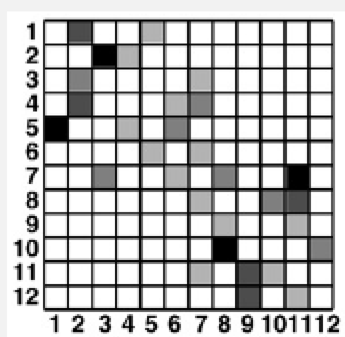
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Subjects	Thresholds	Networ...	Windo...	Windo...	Windo...	Windo...	Windo...	Windo...	Windo...	Windo...	Windo...	Windo...	Windo...
2	sample_01	0.4500	Frag	0	1	1	1	1	1	0	0	0	0	1
3	sample_02	0.4500	Frag	0	0	0	0	0	0	0	0	0	1	1
4	sample_03	0.4500	OK	0	0	0	0	0	0	0	0	0	0	0
5	sample_04	0.4500	Frag	1	1	1	1	1	1	1	1	1	1	1
6	sample_05	0.4500	Frag	1	0	0	0	0	0	1	0	0	0	0
7	sample_06	0.4500	Frag	1	1	1	1	1	1	1	1	1	1	1
8	sample_07	0.4500	Frag	0	0	1	1	1	1	1	1	1	1	1
9	sample_08	0.4500	Frag	0	0	1	0	1	0	0	1	1	0	0
10	sample_09	0.4500	Frag	1	0	0	0	0	0	0	0	0	0	1
11	sample_10	0.4500	Frag	0	0	0	0	0	0	1	0	0	0	0
12	sample_01	0.4600	Frag	0	1	1	1	1	1	0	0	0	0	1
13	sample_02	0.4600	Frag	0	0	0	0	0	0	0	0	0	1	1
14	sample_03	0.4600	OK	0	0	0	0	0	0	0	0	0	0	0
15	sample_04	0.4600	Frag	1	1	1	1	1	1	1	1	1	1	1
16	sample_05	0.4600	Frag	1	0	0	0	0	0	1	0	0	0	0
17	sample_06	0.4600	Frag	1	1	1	1	1	1	1	1	1	1	1
18	sample_07	0.4600	Frag	0	0	1	1	1	1	1	1	1	1	1
19	sample_08	0.4600	Frag	0	0	1	0	1	0	0	1	1	0	0
20	sample_09	0.4600	Frag	1	0	0	0	0	0	0	0	0	0	1
21	sample_10	0.4600	OK	0	0	0	0	0	0	0	0	0	0	0
22	sample_01	0.4700	Frag	0	1	1	1	1	1	0	0	0	0	1
23	sample_02	0.4700	Frag	0	0	0	0	0	0	0	0	0	1	1

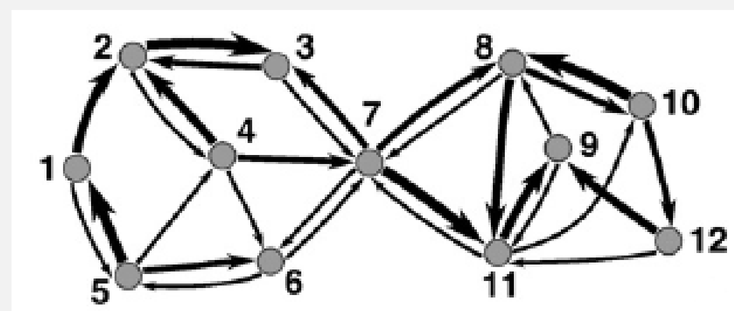


structural datasets: tract tracing
effective datasets: inference of causality
from functional data



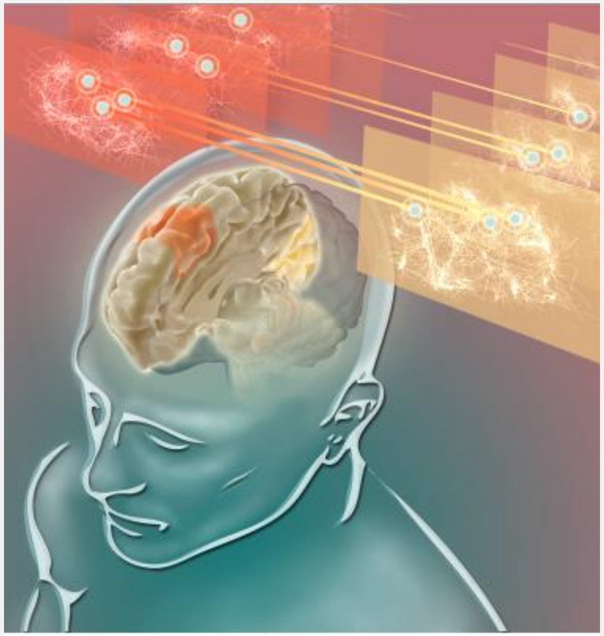
weighted directed networks





Added the directed BCT functions

Network Community Toolbox



http://commdetect.weebly.com/

time-dependent network flexibility

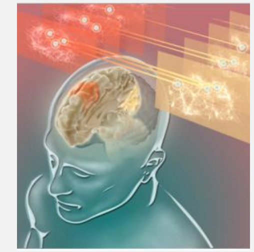
time-dependent nodal promiscuity

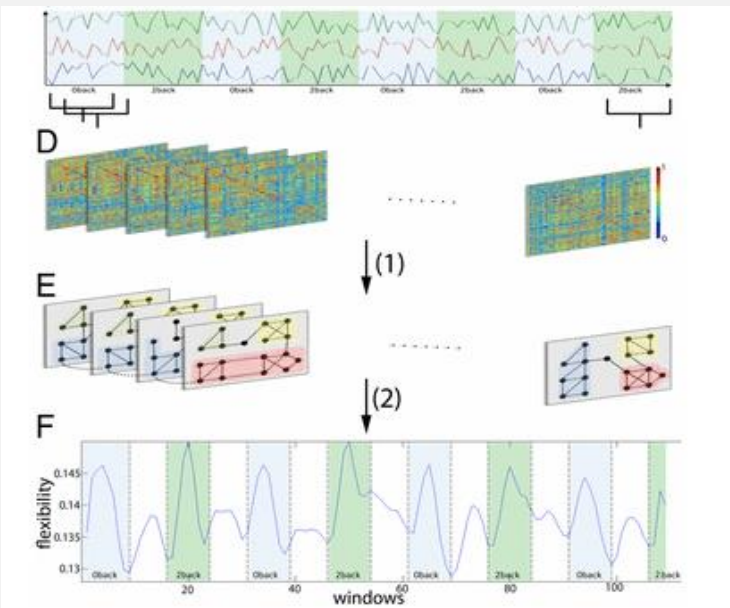
Added two new measures from „Network Community Toolbox“

Institution: Medizinische Bibliothek des Universitaetsklinikums Charite
Proceedings of the National Academy of Sciences of the United States of America
PNAS

Dynamic reconfiguration of frontal brain networks during executive cognition in humans

Urs Braun[a,1], Axel Schäfer[a,1], Henrik Walter[b,1], Susanne Erk[b], Nina Romanczuk-Seiferth[b], Leila Haddad[a], Janina I. Schweiger[a], Oliver Grimm[a], Andreas Heinz[b], Heike Tost[a], Andreas Meyer-Lindenberg[a,1], and Danielle S. Bassett[c,d,1,2]





time-dependent network flexibility:
the time-dependent flexibility of a region is defined as the probability that a brain region changed its allegiance to putative functional modules between any two consecutive time windows. Intuitively, flexibility can be thought of as a statistic to quantify the amount of reconfiguration in functional connectivity patterns that a brain region displays over time (Braun et al., 2015).

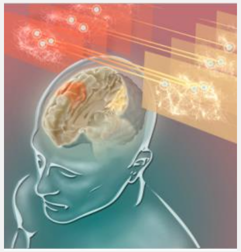
GraphVar uses the generalized Louvain algorithm – so please cite:

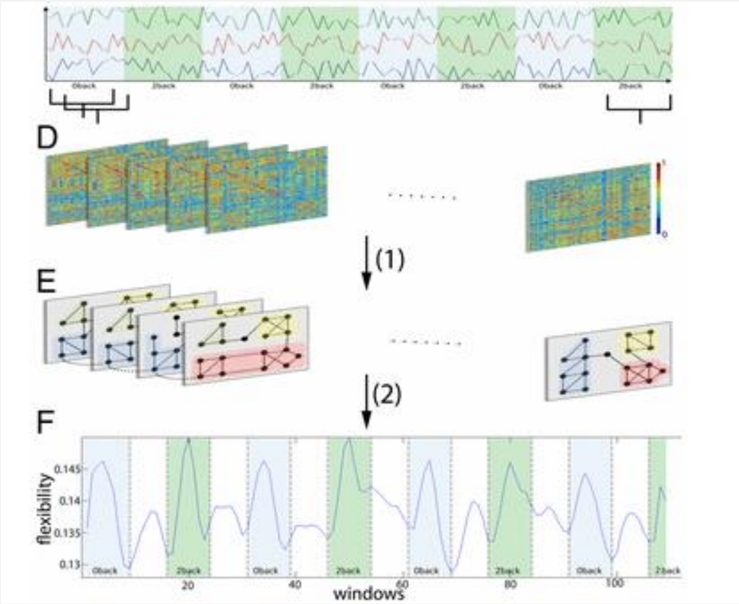
Inderjit S. Jutla, Lucas G. S. Jeub, and Peter J. Mucha, "A generalized Louvain method for community detection implemented in MATLAB," http://netwiki.amath.unc.edu/GenLouvain (2011-2014).

Mucha PJ, Richardson T, Macon K, Porter MA, Onnela JP (2010) Community structure in time-dependent, multiscale, and multiplex networks. Science 328(5980):876–878.

I: „dynamic“ nodal flexibility as in Braun et al. 2015

Network Community Toolbox





time-dependent nodal promiscuity:

This function calculates the promiscuity coefficient.
The promiscuity of a temporal or multislice network corresponds to the fraction of all the communities in the network in which a node participates at least once.

GraphVar uses the generalized Louvain algorithm – so please cite:

Inderjit S. Jutla, Lucas G. S. Jeub, and Peter J. Mucha, "A generalized Louvain method for community detection implemented in MATLAB," http://netwiki.amath.unc.edu/GenLouvain (2011-2014).

Mucha PJ, Richardson T, Macon K, Porter MA, Onnela JP (2010) Community structure in time-dependent, multiscale, and multiplex networks. Science 328(5980):876–878.

II: „dynamic“ nodal promiscuity“ as http://commdetect.weebly.com/

Network Community Toolbox

http://commdetect.weebly.com/

time-dependent network flexibility

time-dependent nodal promiscuity

if normalization with random network is performed NaN´s may result as these measures can produce zeros as results

(e.g. promiscuity P = 0 if it only participates in one community and P=1 if it participates in every community of the network)

… thus check your results in the interim results folder:

multislice_community_assignment_slicesXnodes.mat
multislice_community_assignment_slicesXnodes-rand.mat

Added two new measures from „Network Community Toolbox“

Small-World-Propensity: unbiased assessment of small-world structure in networks of varying densities - developed by Muldoon, Bridgeford and Bassett

Cornell University Library

arXiv.org > q-bio > arXiv:1505.02194

Quantitative Biology > Neurons and Cognition

Small-World Propensity in Weighted, Real-World Networks

Sarah Feldt Muldoon, Eric W. Bridgeford, Danielle S. Bassett

(Submitted on 8 May 2015)

Quantitative descriptions of network structure in big data can provide fundamental insights into the function of interconnected complex systems. Small-world structure, commonly diagnosed by high local clustering yet short average path length between any two nodes, directly enables information flow in coupled systems, a key function that can differ across conditions or between groups. However, current techniques to quantify small-world structure are dependent on nuisance variables such as density and agnostic to critical variables such as the strengths of connections between nodes, thereby hampering accurate and comparable assessments of small-world structure in different networks. Here, we address both limitations with a novel metric called the Small-World Propensity (SWP). In its binary instantiation, the SWP provides an unbiased assessment of small-world structure in networks of varying densities. We extend this concept to the case of weighted networks by developing (i) a standardized procedure for generating weighted small-world networks, (ii) a weighted extension of the SWP, and (iii) a stringent and generalizable method for mapping real-world data onto the theoretical model. In applying these techniques to real world brain networks, we uncover the surprising fact that the canonical example of a biological small-world network, the *C. elegans* neuronal network, has strikingly low SWP in comparison to other examined brain networks. These metrics, models, and maps form a coherent toolbox for the assessment of architectural properties in real-world networks and their statistical comparison across conditions.

http://arxiv.org/pdf/1505.02194v1.pdf

Requires the Bioinformatics Toolbox

Added also Small-World-Propensity

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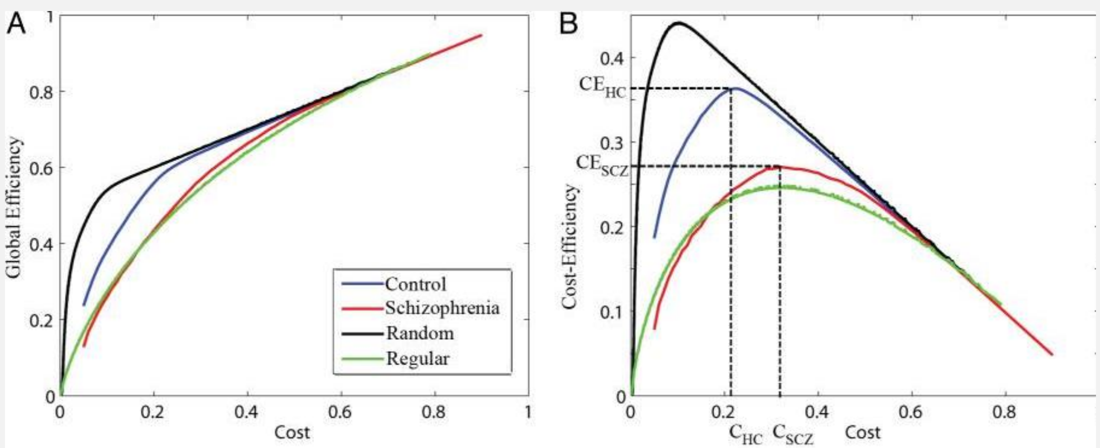
PNAS
Proceedings of the National Academy of Sciences of the United States of America

Proc Natl Acad Sci U S A. 2009 Jul 14; 106(28): 11747–11752.
PMCID: PMC2703669
Published online 2009 Jun 29. doi: 10.1073/pnas.0903641106
Neuroscience

Cognitive fitness of cost-efficient brain functional networks

Danielle S. Bassett,[a,b,c] Edward T. Bullmore,[b,d,1] Andreas Meyer-Lindenberg,[e] José A. Apud,[a] Daniel R. Weinberger,[a] and Richard Coppola[f]



Added also Cost-Efficieny as in Bassett et al., 2009

- GraphVar saves more output files when doing sliding window analyses (not only the dynamic summary measure as before) and will also save all results when only "calculate and Export" for further usage.

Files in your interim results folder are (depending on the computations –
here with clustering_coefficient as example):

- **clustering_coef_bu_4.9_1.mat**: dynamic summary measure (e.g. variance) of clustering_coef_bu across windows for each node on threshold 0.49 for all subjects
- **clustering_coef_bu_4.9_1per_SW.mat**: the (normalized) clustering_coef_bu for each node in each of the sliding windows on threshold 0.49 for all subjects
- **clustering_coef_bu_4.9_1-rand1.mat**: dynamic summary measure (e.g. variance) of clustering_coef_bu across windows for each node in the first random network on threshold 0.49 for all subjects
- **clustering_coef_bu_4.9_1-rand_per_SW.mat**: the clustering_coef_bu for each node in each random network in each of the sliding windows on threshold 0.49 for all subjects (i.e., cell comprised of: subjects x random networks x sliding windows)

More output for further usage