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 useful in sliding window analyses (if you want to make sure that all nodes are always part of the network)

... this may also be useful in finding „strange“ subjects (e.g. bad data)
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“
Dynamic reconfiguration of frontal brain networks during executive cognition in humans

Urs Braun\textsuperscript{a,1}, Axel Schäfer\textsuperscript{a,1}, Henrik Walter\textsuperscript{b,1}, Susanne Erk\textsuperscript{b}, Nina Romanczuk-Seiferth\textsuperscript{b}, Leila Haddad\textsuperscript{a}, Janina I. Schweiger\textsuperscript{a}, Oliver Grimm\textsuperscript{a}, Andreas Heinz\textsuperscript{b}, Heike Tost\textsuperscript{e}, Andreas Meyer-Lindenberg\textsuperscript{a,1}, and Danielle S. Bassett\textsuperscript{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,


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


Added two new measures from „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
Small-World-Propensity: unbiased assessment of small-world structure in networks of varying densities - developed by Muldoon, Bridgeford and Bassett

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.


Requires the Bioinformatics Toolbox

Added also Small-World-Propensity
Added also Cost-Efficiency as in Bassett et al., 2009
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)