Supporting Information : Text S1

NC Algorithm Summary

Input: (i) A raster of activation data, recorded as (time,node) pairs, i.e. (t_e, s_e) ; (ii) p-value for the reconstruction, p.

Output: The reconstructed weighted directed network

- 1. Determine the rule by which the n_a source nodes will be chosen for every target node. In our current implementation in reconstructing networks from neuronal avalanches, we took the approach developed in [29, 30] in which the events were binned with a time window Δt chosen as a mean of the time-interval distribution from successively activated nodes in the network. In this particular case, only nodes in the preceding time bin are treated as the potential source nodes. Thus, the raster becomes a $N_t \times N$ sparse matrix, where $N_t = T_{exp}/\Delta t$ is the total number of time bins.
- 2. Determine the number of propagation steps, N_p , i.e. number of the incidences in which each of the two successive time-bins contains at least one active node. This number should be greater than the number of potential links in the network (N(N-1)) (Figure 4A)
- 3. Evaluate the NC_{ij} factor for all links, according to Equation 18. If highly supercritical dynamics is suspected, the more general Eqs. 14 and 15 should be used.
- 4. Use pair-wise shuffling (subsection "Shuffling" in the Methods) to produce $N_R = f_o/p$ replicates of the raster, where $f_o > 1$ (see Methods). For each replicate r and each link $i \to j$ determine the factor $\mathrm{NC}_{ij}^{(r)}$ using Equation 18. From the PDF of $\mathrm{NC}_{ij}^{(r)}$ and the given confidence level p determine $\mathrm{NC}_{ij}^{(p)}$.
- 5. From NC_{ij} and $NC_{ij}^{(p)}$, obtain the reconstructed network topology and weights according to Eqs. 20 and 21.

Additional steps might include validating the reconstruction by varying the length of the raster records used, to ensure that the reconstruction is not dependent on N_p . The implementation of this algorithm was done in C and in Matlab. The pre-compiled version of this code will be made available upon publication at http://mscl.cit.nih.gov/spaj (link to PWAnetrec).

List of Abbreviations

aCSF	 artificial cerebrospinal fluid
BA	 Barabasi-Alberts network [46]
DSPR	 degree sequence preserving randomization
\mathbf{ER}	 Erdös-Rényi network (or randomization scheme)
\mathbf{FC}	 Frequency Count reconstruction approach
IB	 Iterative Bayesian approach
MEA	 Multi-Electrode Array (Multichannelsystems, Germany)
NC	 Normalized Count approach
OHO	 Ozik-Hunt-Ott (OHO) network [48]
PWA	 Posterior Weighted Averaging
SS	 Single Source approach
STES	 Single Target Estimation Step; a simple Bayesian estimation step con-
	sisting of a single target node at a particular time instance and a subset
	of potential source nodes.
WN	 Watts-Newman (modified Watts-Strogatz) network

Mathematical Notation

\mathcal{O}	 generic symbol designating an observation, i.e. a pattern of activations
\mathcal{N}	 generic symbol designating a network
\mathcal{N}_{c}	 instance of network topology (adjacency matrix). For STES it is a particular
	configuration by which source nodes connect to the target node (Figure 1E)
n_a	 number of active source nodes considered in STES
$\langle n_a \rangle$	 average n_a over all STES in a given experiment
n_c	 number of active source nodes that connect to the target node in a particular
	\mathcal{N}_c being considered
p_l	 probability that a given link l exists in IB; also a link prior
p_t	 threshold for p_l in IB; link exists if $p_l \ge p_t$
p_b	 uniform prior probability for link existence used in PWA
$p(\mathcal{N}_c)$	 prior probability of a given network configuration \mathcal{N}_c
$p(\mathcal{O} \mathcal{N}_c)$	 likelihood term (here called <i>dynamics</i> term) in Bayesian reconstruction
p_D^c	 dynamics term for a particular configuration \mathcal{N}_c
П	 generic designation for posterior probabilities
p^{Π}	 generic term for posterior probability for links
p_l^{Π}	 posterior value of p_l obtained for link l within IB iteration using Equation
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$\Pi_c(n_c, n_a)$	 the posterior probability of a particular network configuration \mathcal{N}_c , having
	n_c existing links out of n_a possible links
$\mathcal{P}(n_c, n_a)$	 compounded the dynamics and the prior terms, $p_D(n_c)p_r(n_c, n_a)$
\mathcal{N}_R	 network obtained through reconstruction from the dynamics

$\mathcal{N}_{R}^{ ext{NC}}$ $\mathcal{N}_{R}^{ ext{IB}}$ $n_{a}^{ ext{max}}$	 network obtained by the normalized-count (NC) approach
$\mathcal{N}_{\mathbf{D}}^{\mathbf{n}}$	 network obtained by the Iterative Bayesian (IB) approach
n^{\max}	 cut-off value for n_a in IB reconstruction above which the corresponding
n_a	STES is skipped
N_p	 number of propagation steps in a time-binned raster, i.e. number of times
1 V p	that both of the successive time-bins contain at least one active site
$N_{ m stes}$	 total number of STES used in reconstruction
t	 index into individual time bins, or STES
t_i	 time of an event "i" occurred, or for a particular STES, an event that
ι_i	occurred on the i^{th} node
Λ	amplitude of an event "i", or the one occurring on the i^{th} node
A_i	
p_{ij}	 activation probability for the link $i \rightarrow j$; a fixed probability that an active
	source node i will activate its target node j in the avalanche dynamics
$p_F()$	 function that represents a-priori knowledge of the continuous time branch-
	ing process dynamics, and describes how the timing of the events (in most
	cases only the timing differences, $t_j - t_i$ and amplitudes of the events A
F	affect the original activation probabilities, p_{ij} .
p_{ij}^F	 predicted probability for the $i \rightarrow j$ activation, obtained using a-priori knowl-
	edge contained in $p_F()$
p_d	 mean-field approximation to our branching process dynamics, $p_d = \langle p_{ij} \rangle$,
_	or just a uniform activation probability
p_d^c	 critical value of the probability p_d
w_{ij}	 weight of a directed link $i \to j$
a_{ij}	 binary indicator of the existence of a link $i \to j$
$m~(m_{\scriptscriptstyle \mathrm{BA}},m_{\scriptscriptstyle \mathrm{OHO}})$	 number of edges added in growing networks, OHO and BA
m_0	 initial number of nodes in growing networks
K	 number of the nearest neighbors $(2K)$ that a node connects to in WN
_	network
w^{Π}	 weighting factor in PWA
σ_d	 the branching parameter, which determines the dynamical regime
$\Pi_{ m norm}$	 the normalization term for the posterior probability
$\{s_l\}$	 source node index that connects to the target through the l^{th} link
$W_{ m norm}$	 normalization factor for PWA weighted measures
$V_{ m norm}$	 normalization factor for a correlation measure
Δt	 the width of a time window at which events were binned
z, σ_A	 parameters determining the heterogeneity of the branching process initia-
,	tion
N	 number of nodes in a network
k_d	 degree of a particular node
C	 clustering coefficient of a network
$\langle k_d \rangle$	 average node degree for the whole network
$\langle d \rangle$	 average node-to-node distance
$C_{\rm ER}$	 C of the randomized network using ER randomization
$C_{\rm DSPR}$	 C of the randomized network using DSPR randomization
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p_S	 edge density, or sparsity of network, defined as $p_S = \# \text{links}/(N(N-1))$
$p_{ m ER}$	 probability that a link exist in Erdös-Rényi network
$p_{ m WN}$	 probability that a random link exist in Watts-Newman network
p_{ext}	 in our simulations, the probability that the node activation is caused by
	noise
FC_{ij}	 frequency of successive activations between the nodes i and j
WC_{ii}	 weighted measure of successive activations between the nodes i and j
$ \begin{array}{c} \mathrm{WC}_{ij} \\ \mathrm{NC}_{ij} \\ \mathrm{NC}_{ij}^{(E)} \end{array} $	 scalar measure assigned to each link according to Equation 18
$\mathrm{NC}_{ii}^{(E)}$	 scalar measure assigned to each link, similar to NC_{ij} but with a weighting
ιj	factor according to Equation 14
$\mathrm{NC}_{ij}^{(A)}$	 the simplest approximation of $NC_{ij}^{(E)}$ which keeps the branching parameter
$1 \cdot \circ ij$	σ_d (Equation 15)
$NC^{(E)}$	 NC method which uses $NC_{ij}^{(E)}$ instead of NC_{ij} NC method which uses $NC_{ij}^{(A)}$ instead of NC_{ij}
$NC^{(A)}$	 NC method which uses $NC_{ij}^{(A)}$ instead of NC_{ij}
p	 p-value, confidence level in network reconstruction
$\mathrm{NC}_{ij}^{(r)} \ \mathrm{NC}_{ij}^{(p)}$	 NC_{ij} values obtained from surrogate data sets using shuffling
$\mathrm{NC}_{ij}^{(p)}$	 the threshold value for NC_{ij} at the significance level p , obtained from the
5	empirical distribution of $NC_{ij}^{(r)}$
n_S	 number of cascade events switches in pair-wise shuffling
N_R	 number of replicates obtained with pair-wise shuffling
f_o	 over-shuffling factor that increases N_R for a given p , for better estimation
	of $NC_{ij}^{(p)}$
E_p	 measure of the reconstruction error, defined in Equation
$E_{\rm tot}$	 reconstruction error relative to all possible links, $N(N-1)$
$E_{ m tot} = E_U$	 the percent difference between two topologies, quantified as the total num-
	ber of differences divided by the number of links that exist in either of the
	two (range: 0-100%)
$ ho_I, ho_U$	 correlation between two architectures using the links that exist in both
	networks (intersect, ρ_I), or in either network (union, ρ_U)
$E_D^{\scriptscriptstyle \mathrm{ER}}, \rho_I^{\scriptscriptstyle \mathrm{ER}}, \rho_U^{\scriptscriptstyle \mathrm{ER}}$	 measures E_U , ρ_I , and ρ_U obtained by comparing the ER randomized net-
-	works