Text Supplementary 1 – Unraveling Spurious Properties of Interaction Networks with Tailored Random Networks

Stephan Bialonski^{1,2,3,}*, Martin Wendler⁴, Klaus Lehnertz^{1,2,3}

1 Department of Epileptology, University of Bonn, Bonn, Germany

2 Helmholtz Institute for Radiation and Nuclear Physics, University of Bonn, Bonn, Germany

3 Interdisciplinary Center for Complex Systems, University of Bonn, Bonn, Germany

4 Fakult¨at f ¨ur Mathematik, Ruhr-Universit¨at Bochum, Bochum, Germany

∗ **E-mail: bialonski@gmx.net**

Lemma 1

For every $i, j \in \{1, \ldots, N\}$ with $i \neq j$, we have the following limit of the probability distribution of the empirical correlation:

$$
P\left(\sqrt{\frac{T}{g(M)}}\text{corr}(x_{i,M,T}, x_{j,M,T}) \leq x\right) \to \Phi(x) \quad \text{with } g(M) = \frac{2}{3}M + \frac{1}{3}\frac{1}{M} \tag{1}
$$

as $T \rightarrow \infty$, where Φ denotes the cumulative distribution function of a standard normal random variable.

Proof

In order to simplify the presentation, we write $y_{i,M,T}(t) = x_{i,M,T}(t) - \frac{1}{2}$, so that $Ey_{i,M,T}(t) =$ 0. First note that $y_{i,M,T}(t)$ is a *M*-dependent sequence, i.e. for $|s-t| > M$, $y_{i,M,T}(s)$ and $y_{i,M,T}(t)$ are independent. So we have that the covariance

$$
Cov(y_{i,M,T}(1)y_{j,M,T}(1), y_{i,M,T}(t)y_{j,M,T}(t)) = 0 \quad \text{for } T > M.
$$

Additionally,

Cov
$$
(y_{i,M,T}(1)y_{j,M,T}(1), y_{i,M,T}(t)y_{j,M,T}(t)) =
$$

Cov $(y_{i,M,T}(1), y_{i,M,T}(t))$ Cov $(y_{j,M,T}(1), y_{j,M,T}(t))$ (2)

and $Cov(z_i(s), z_i(t)) = Var(z_i(1))$ if $s = t$ and otherwise $Cov(z_i(s), z_i(t)) = 0$. For $1 \le t \le M$, we obtain by the definition of the moving average and the independence of the underlying process $z_i(t)$, $t \in \mathbb{N}$ that

$$
Cov(y_{i,M,T}(1)y_{j,M,T}(1), y_{i,M,T}(t)y_{j,M,T}(t)) = \frac{1}{M^4} \left(\sum_{s=1}^{M-(t-1)} Var(z_j(s)) \right)^2 \tag{3}
$$

$$
= \frac{1}{M^4}(M - (t-1))^2 \text{Var}^2(z_i(1)). \quad (4)
$$

By the central limit theorem for *M*-dependent random variables, see reference [1],

$$
\frac{1}{\sqrt{\text{Var}\left(\frac{1}{T}\sum_{t=1}^{T}y_{i,M,T}(t)y_{j,M,T}(t)\right)}}\frac{1}{T}\sum_{t=1}^{T}y_{i,M,T}(t)y_{j,M,T}(t)
$$
(5)

converges in distribution to a standard normal random varibale as $T \rightarrow \infty$. Furthermore, we have the following convergence for the variance as $T \rightarrow \infty$:

$$
\begin{split} T\text{Var}\left(\frac{1}{T}\sum_{t=1}^{T}y_{i,M,T}(t)y_{j,M,T}(t)\right) \\ \rightarrow \text{Var}(y_{i,M,T}(1)y_{j,M,T}(1)) + 2\sum_{t=2}^{M}\text{Cov}\left(y_{i,M,T}(1)y_{j,M,T}(1), y_{i,M,T}(t)y_{j,M,T}(t)\right) \\ &= \left(\frac{1}{M^2} + \frac{2}{M^4}\sum_{t=2}^{M}(M-(t-1))^2\right)\text{Var}^2\left(z_i(1)\right) = \frac{\mathcal{S}(M)}{M^2}\text{Var}^2\left(z_i(1)\right). \end{split} \tag{6}
$$

The last equality follows easily by $\sum_{i=1}^{n} i^2 = \frac{n(n+1)(2n+1)}{6}$ $\frac{(n+1)}{6}$. With the same central limit theorem, $\frac{1}{\sqrt{2}}$ $\frac{1}{T} \sum_{t=1}^T y_{i,M,T}(t)$ converges to a normal limit, so $\frac{1}{T^{\frac{3}{4}}}$ $\sum_{t=1}^{T} y_{i,M,T}(t) \rightarrow 0$ in probability and consequently

$$
\sqrt{T}\left(\frac{1}{T}\sum_{t=1}^{T}y_{i,M,T}(t)\right)\left(\frac{1}{T}\sum_{t=1}^{T}y_{j,M,T}(t)\right) = \left(\frac{1}{T^{\frac{3}{4}}}\sum_{t=1}^{T}y_{i,M,T}(t)\right)\left(\frac{1}{T^{\frac{3}{4}}}\sum_{t=1}^{T}y_{j,M,T}(t)\right) \to 0 \quad (7)
$$

in probability as T \rightarrow ∞ . By similar arguments, we have that $\frac{1}{T} \sum_{t=1}^{T} y_{i,t}^2$ $\frac{2}{i}$,*M*,*T*</sub>(*t*) → $Var(y_{i,M,T}(1)) = \frac{1}{M}Var(z_i(1))$ and $\frac{1}{T}\sum_{t=1}^{T}y_{i,M,T}(t) \to 0$, so we get

$$
\frac{1}{T} \sum_{t=1}^{T} (y_{i,M,T}(t) - \bar{y}_{i,M,T})^2 = \frac{1}{T} \sum_{t=1}^{T} y_{i,M,T}^2(t) - \left(\frac{1}{T} \sum_{t=1}^{T} y_{i,M,T}(t)\right)^2
$$

$$
\to \text{Var}(y_{i,M,T}(1)) = \frac{1}{M} \text{Var}(z_i(1)). \tag{8}
$$

By Slutsky's theorem [2] and with (5), (6), (7), and (8), we finally obtain that

$$
\sqrt{\frac{T}{g(M)}} \text{corr}(x_{i,M,T}, x_{j,M,T})
$$
\n
$$
= \frac{\sqrt{T_{T}^{1} \sum_{t=1}^{T} y_{i,M,T}(t) y_{j,M,T}(t) - \sqrt{T} \left(\frac{1}{T} \sum_{t=1}^{T} y_{i,M,T}(t)\right) \left(\frac{1}{T} \sum_{t=1}^{T} y_{j,M,T}(t)\right)}{\sqrt{g(M)_{T}^{1} \sum_{t=1}^{T} (y_{i,M,T}(t) - \bar{y}_{i,M,T})^{2} \frac{1}{T} \sum_{t=1}^{T} (y_{j,M,T}(t) - \bar{y}_{j,M,T})^{2}}}
$$
\n(9)

converges in distribution to a standard normal random variable as $T \rightarrow \infty$. This completes the proof.

Lemma 2

For $T \to \infty$, $R \to \infty$ *ǫ*ˆ *θ* $\sqrt{T_{\text{eff}}(M)}$, *M*, *T* \setminus $\rightarrow 2\Phi(-\theta)$ (10)

in probability with $T_{\text{eff}}(M) = \frac{T}{g(M)}$.

Proof

With Lemma 1, we have that

$$
E\left[H_{ij,M,T}^{(r)}\left(\frac{\theta}{\sqrt{T_{\text{eff}}(M)}}\right)\right] = P\left(\rho_{ij,M,T} > \frac{\theta}{\sqrt{T_{\text{eff}}(M)}}\right)
$$

= $P\left(\text{corr}(x_{i,M,T}, x_{j,M,T}) > \frac{\theta}{\sqrt{T_{\text{eff}}(M)}}\right) + P\left(\text{corr}(x_{i,M,T}, x_{j,M,T}) < \frac{-\theta}{\sqrt{T_{\text{eff}}(M)}}\right)$
= $P\left(\sqrt{\frac{T}{g(M)}}\rho_{ij,M,T} > \theta\right) + P\left(\sqrt{\frac{T}{g(M)}}\rho_{ij,M,T} < -\theta\right) \to 2\Phi(-\theta)$

as $T \rightarrow \infty$. Furthermore*,* $H_{ij,l}^{(r)}$ $f^{(r)}_{ij,M,T}$ is bounded by 0 and 1, so Var $\left(H^{(r)}_{ij,M}\right)$ *ij*,*M*,*T* $\Big) \leq \frac{1}{4}$. By the independence of the *R* random networks

$$
\text{Var}\left(\hat{\epsilon}\left(\frac{\theta}{\sqrt{T_{\text{eff}}(M)}}, M, T\right)\right) = \frac{1}{R^2} \sum_{r=1}^{R} \text{Var}\left(H_{ij,M,T}^{(r)}\left(\frac{\theta}{\sqrt{T_{\text{eff}}(M)}}\right)\right) \le \frac{1}{4R} \to 0 \quad (11)
$$

as $R \rightarrow \infty$. The lemma follows with the Chebyshev inequality.

References

- 1. Hoeffding W, Robbins H (1948) The central limit theorem for dependent random variables. Duke Math J 15: 773-780.
- 2. Slutsky E (1925) Über stochastische Asymptoten und Grenzwerte (in german). Metron 5: 3–89.