Estimation of Neural Connections from Multiple Spike Trains

graph structure inference with nuisance inputs

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Introduction

estimating neural connections:

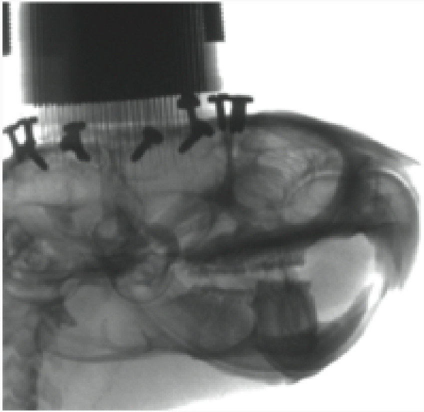
- understand functions of biological systems
- investigate learning/adaptation mechanisms

typical methods for measuring brain activities:

- fMRI (functional magnetic resonance imaging)
- MEG (magnetoencephalography)
- EEG (electroencephalography)
- TPE (two-photon excitation microscopy)
- multi-electrode recording

different resolutions in:

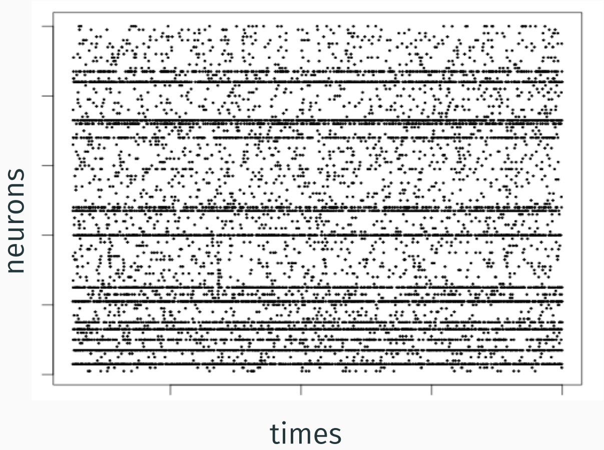
- time (oxygen consumption - neuron firing)
- space (brain mapping - synaptic connections)



by courtesy of Dr. Tatsuno
at University of Lethbridge

activities of individual neurons:

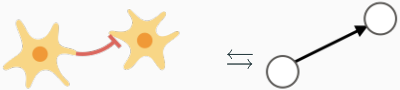
- multiple neurons
  (tens - hundreds)
- long term measurement
  (several hours - several days)

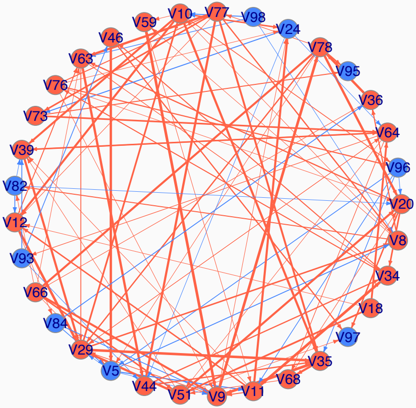


rearranged as binary sequence indicating states of neurons:

- 0: resting
- 1: firing

multi-variate binary time series contains information of neural interactions





mathematical representation - directed graph

- node: neuron
- edge: synaptic connection

objective

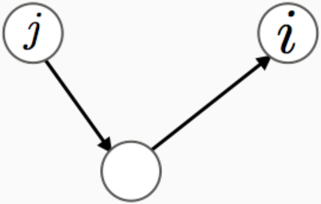
estimate weights of edges from binary time series at nodes typical methods for analysis:

- pair-wise:
  - cross-correlation (e.g. Wilson and McNaughton 1994)
  - joint peri-stimulus time histogram (e.g. Ito and Tsuji 2000)
- graph-based:
  - sparse inverse covariance matrix (e.g. Friedman, Hastie, and Tibshirani 2008)
  - digraph Laplacian (e.g. Noda et al. 2014)
- higher-order:
  - information geometric measure (e.g. Nakahara and Amari 2002; Tatsuno, Fellous, and Amari 2009)
  - Granger causality (e.g. Kim et al. 2011)

- pseudo correlation caused by higher-order effects
- influence from unobserved neurons
- directed excitatory/inhibitory connections

correlation coefficient:

statistics for analyzing relation of two random variables



connections

- no direct relation exists
- two nodes are connected with the same node

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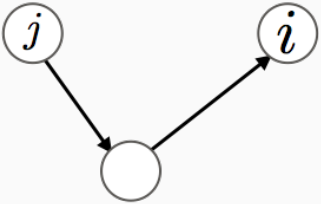

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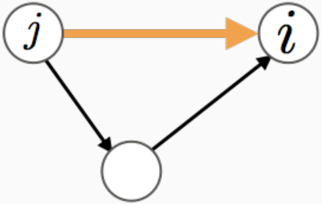

pseudo-correlation

- spurious relation appears

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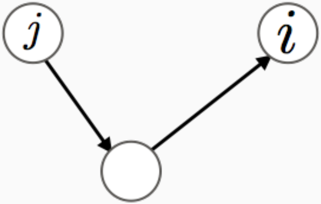

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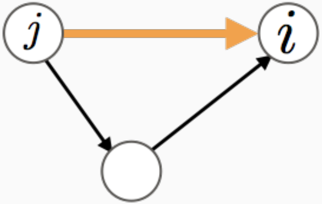

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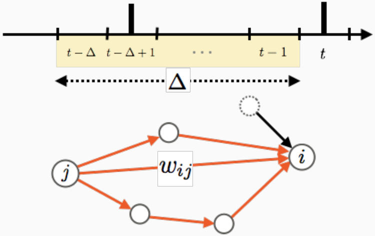
- spurious relation appears

pseudo correlation

a common problem in complex network analysis

delayed correlation coefficient:

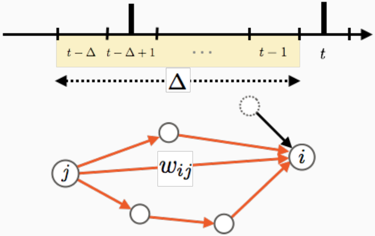
statistics for analyzing time series / dynamical systems

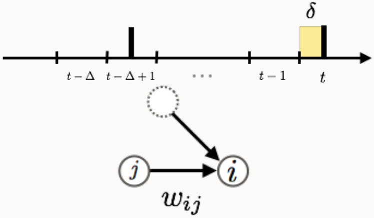


- appropriate intervals have to be considered
- information propagates multiple paths
- spurious relation appears

delayed correlation coefficient:

statistics for analyzing time series / dynamical systems





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- consider short intervals?

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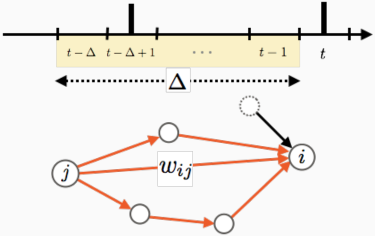

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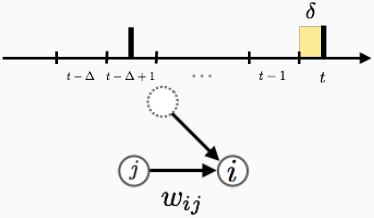

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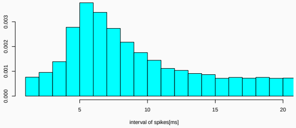

- spike intervals are random

a mathematical framework for treating:

- pseudo correlation caused by higher-order effects
- influence from unobserved neurons
- directed excitatory/inhibitory connections

a mathematical framework for treating:

- pseudo correlation caused by higher-order effects
- influence from unobserved neurons
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main contribution

solve those problems with simple mathematical tricks

Problem Formulation

indeces:

- $i \in \{1, 2, \ldots, N\}$: index of neurons
- $t \in \{1, 2, \ldots, T\}$: discrete time of measurement
- $t_\Delta = [t - \Delta, \ldots, t - 1]$: interval for delayed correlation

states:

- $X_i(t) \in \{0, 1\}$: state of neuron i at time t
- $X_i[t_\Delta] \in \{0, 1\}$: state of neuron i in interval t_Δ
- $U_i(t) \in \mathbb{R}$: internal state of neuron i at time t

connections:

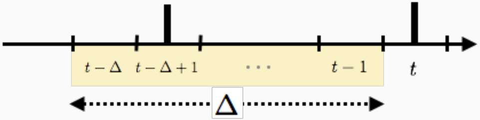
- $w_{ij} \in \mathbb{R}$: synaptic connection from neuron j to neuron i
- $\lambda_{ij} \in \mathbb{R}$: pseudo connection from neuron j to neuron i

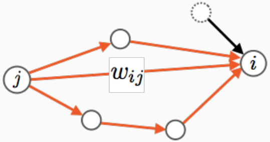
weighted sum of inputs from unobserved/observed neurons:

$$U_i(t) = B_i(t) + \sum_{j=1}^{N} \lambda_{ij} X_j[t_\Delta],$$

$B_i(t)$: nuisance inputs from unobserved neurons

λ_{ij} : pseudo connection including undirect paths





remarks

- signal from neuron j has several paths
- λ_{ij} includes direct and undirect connections

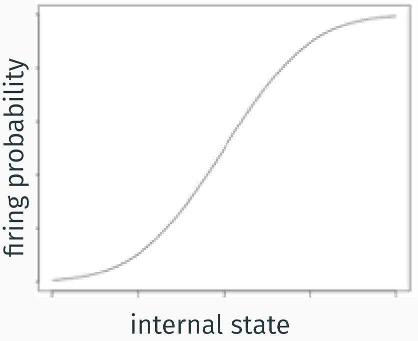
stochastic dependency on internal state:

$$\Pr\big(X_i(t) = 1\big) = \Phi_{\sigma^2}\big(U_i(t)\big),$$
$$\Phi_{\sigma^2} : \text{cdf of } \mathcal{N}(0, \sigma^2).$$

model assumption

- we assume a probit model
- Φ_{σ^2} is the integral of

$$\phi_{\sigma^2}(z) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{z^2}{2\sigma^2}\right)$$



internal state:

$$U_i(t) = B_i(t) + \sum_{j=1}^{N} \lambda_{ij} X_j[t_\Delta],$$

$B_i(t)$: nuisance inputs,

λ_{ij} : pseudo connection.

neuron firing:

$$\Pr\big(X_i(t) = 1\big) = \Phi_{\sigma^2}\big(U_i(t)\big),$$

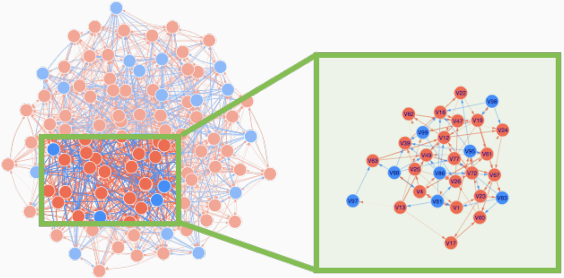
$$\phi_{\sigma^2}(z) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{z^2}{2\sigma^2}\right),$$

Φ_{σ^2} : cdf of $\mathcal{N}(0, \sigma^2)$, integral of ϕ_{σ^2}.

first step

remove nuisance input B and estimate pseudo connection λ

$$U_i(t) = B_i(t) + \sum_{j=1}^{N} \lambda_{ij} X_j[t_\Delta].$$



Theorem

Let X and Y be independent random variables. For any function g, we have

$$\mathbb{E}[g(X+Y)] = \mathbb{E}\left[h\left(X+\mathbb{E}[Y]\right)\right],$$

where f_Y is the pdf of Y and

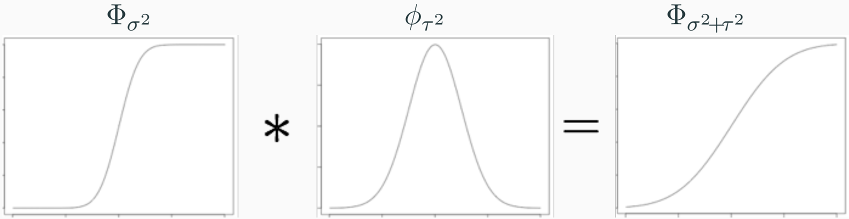
$$\begin{aligned} f_Y^-(x) &= f_Y(\mathbb{E}[Y]-x), \\ h &= g * f_Y^-. \end{aligned}$$

A special case is discussed in Hyvärinen 2002.

Corollary

If the function g is Φ_{σ^2} and random variable X is constant value x, and probability density function f_Y is Gaussian with mean $\mathbb{E}[Y]$ and variance τ^2, we have

$$\mathbb{E}[\Phi_{\sigma^2}(x+Y)] = \Phi_{\sigma^2+\tau^2}\left(x+\mathbb{E}[Y]\right).$$



consider the case of $X_j[t_\Delta] = 1$:

$$U_i(t \mid X_j[t_\Delta] = 1) = B_i(t) + \lambda_{ij} X_j[t_\Delta] + \sum_{k \neq j} \lambda_{ik} X_k[t_\Delta]$$
$$= \lambda_{ij} + C_{ij}\big(t \mid X_j[t_\Delta] = 1\big).$$

consider the case of $X_j[t_\Delta]=1$:

$$
\begin{aligned}
U_i(t \mid X_j[t_\Delta]=1) &= B_i(t) + \lambda_{ij} X_j[t_\Delta] + \sum_{k \neq j} \lambda_{ik} X_k[t_\Delta] \\
&= \lambda_{ij} + C_{ij}\big(t \mid X_j[t_\Delta]=1\big).
\end{aligned}
$$

apply the corollary for calculating conditional expectation:

$$
\begin{aligned}
\mathbb{E}\big[X_i(t) \mid X_j[t_\Delta]=1\big] &= \mathbb{E}\big[\Phi_{\sigma^2}\big(U_i(t \mid X_j[t_\Delta]=1)\big)\big] \\
&= \mathbb{E}\big[\Phi_{\sigma^2}\big(\lambda_{ij} + C_{ij}(t \mid X_j[t_\Delta]=1)\big)\big] \\
&= \Phi_{\rho^2}(\lambda_{ij} + \bar{C}_{ij}),
\end{aligned}
$$

where we assume $C_{ij} \sim \mathcal{N}(\bar{C}_{ij}, \tau^2)$ and $\rho^2 = \sigma^2 + \tau^2$.

for binary random variables,

$$\mathbb{E}\left[\mathsf{X}_i(\mathsf{t}) \mid \mathsf{X}_j[\mathsf{t}_\Delta]{=}1\right] = \Pr(\mathsf{X}_i(\mathsf{t}){=}1 \mid \mathsf{X}_j[\mathsf{t}_\Delta]{=}1).$$

holds, therefore, obtain:

$$\begin{aligned} &\Phi_{\rho^2}(\lambda_{ij} + \bar{\mathsf{C}}_{ij}) = \Pr(\mathsf{X}_i(\mathsf{t}) = 1 \mid \mathsf{X}_j[\mathsf{t}_\Delta]{=}1), \\ \Leftrightarrow \quad &\lambda_{ij} + \bar{\mathsf{C}}_{ij} = \rho \cdot \Phi_1^{-1}\big(\Pr(\mathsf{X}_i(\mathsf{t}){=}1 \mid \mathsf{X}_j[\mathsf{t}_\Delta]{=}1)\big). \end{aligned}$$

consider the both cases of $X_j[t_\Delta] = 1$ and $X_j[t_\Delta] = 0$:

$$
\begin{aligned}
U_i(t \mid X_j[t_\Delta]{=}1) &= \lambda_{ij} + C_{ij}(t \mid X_j[t_\Delta]{=}1), \\
U_i(t \mid X_j[t_\Delta]{=}0) &= \phantom{\lambda_{ij} +{}} C_{ij}(t \mid X_j[t_\Delta]{=}0).
\end{aligned}
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assumption

$$C_{ij}(t \mid X_j[t_\Delta]{=}1), C_{ij}(t \mid X_j[t_\Delta]{=}0) \sim \mathcal{N}(\bar{C}_{ij}, \tau^2)$$

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\end{aligned}
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C_{ij}(t \mid X_j[t_\Delta]{=}1), C_{ij}(t \mid X_j[t_\Delta]{=}0) \sim \mathcal{N}(\bar{C}_{ij}, \tau^2)
$$

then obtain:

$$
\begin{aligned}
\lambda_{ij} + \bar{C}_{ij} &= \rho \cdot \Phi_1^{-1}\big(\Pr(X_i(t){=}1 \mid X_j[t_\Delta]{=}1)\big), \\
\bar{C}_{ij} &= \rho \cdot \Phi_1^{-1}\big(\Pr(X_i(t){=}1 \mid X_j[t_\Delta]{=}0)\big).
\end{aligned}
$$

estimator of pseudo connection:

$$\lambda_{ij} = \rho\big\{\Phi_1^{-1}\big(\Pr(X_i(t)=1 \mid X_j[t_\Delta]=1)\big) - \Phi_1^{-1}\big(\Pr(X_i(t)=1 \mid X_j[t_\Delta]=0)\big)\big\}.$$

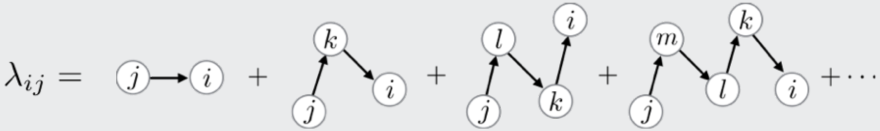
empirical estimates of conditional probability:

$$\Pr(X_i(t)=1 \mid X_j[t_\Delta]=1) = \frac{1}{Z}\sum_t X_i(t \mid X_j[t_\Delta]=1),$$

$$\Pr(X_i(t)=1 \mid X_j[t_\Delta]=0) = \frac{1}{Z'}\sum_t X_i(t \mid X_j[t_\Delta]=0).$$

second step

decompose pseudo connections λ with direct connections w:



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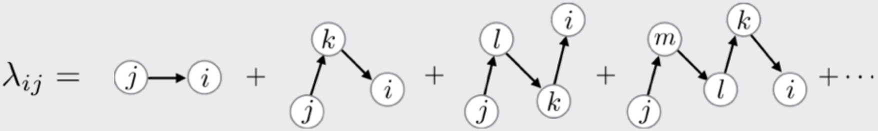

consider an expansion with appropriate δ, δ' (delay time)

$$
\begin{aligned}
\lambda_{ij} &= w_{ij} \\
&\quad + \sum_k w_{ik} \Pr(X_k(t-\delta)=1 \mid X_j(t-\delta')=1) \\
&\quad + \text{(higher order terms)}.
\end{aligned}
$$

introducing a virtual probability with an appropriate interval t_δ

$$\theta_{ij} = \Pr(X_i(t){=}1 \mid X_j[t_\delta]{=}1),$$

obtain an expansion of λ as:

$$\lambda_{ij} = w_{ij} + \sum_k w_{ik}\theta_{kj} + \sum_{k,l} w_{ik}\theta_{kl}\theta_{lj} + \sum_{k,l,m} w_{ik}\theta_{kl}\theta_{lm}\theta_{mj} + \cdots .$$

introducing a virtual probability with an appropriate interval t_δ

$$\theta_{ij} = \Pr(X_i(t) = 1 \mid X_j[t_\delta] = 1),$$

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this expression gives a simple matrix form:

$$\begin{aligned} \Lambda &= W(I + \Theta + \Theta^2 + \Theta^3 + \cdots) \\ &= W(I - \Theta)^{-1}, \end{aligned}$$

▷ Neumann series

where $W = (w_{ij})$ and $\Theta = (\theta_{ij})$.

relation between θ and w:

$$\begin{aligned}
\theta_{ij} &= \Pr(X_i(t)=1 \mid X_j[t_\delta]=1) \\
&= \mathbb{E}\left[\Phi_{\sigma^2}(w_{ij} + C'_{ij})\right] \\
&= \Phi_{\rho^2}\left(w_{ij} + \mathbb{E}[C'_{ij}]\right)
\end{aligned}$$

- ▷ use expectation form
- ▷ t_δ is small enough
- ▷ by the corollary

CC BY SA

relation between θ and w:

$$\begin{aligned}\theta_{ij} &= \Pr(X_i(t) = 1 \mid X_j[t_\delta] = 1) && \triangleright \text{ use expectation form}\\ &= \mathbb{E}\left[\Phi_{\sigma^2}(w_{ij} + C'_{ij})\right] && \triangleright\ t_\delta \text{ is small enough}\\ &= \Phi_{\rho^2}\left(w_{ij} + \mathbb{E}[C'_{ij}]\right) && \triangleright \text{ by the corollary}\end{aligned}$$

assumption

$$C'_{ij} \sim \mathcal{N}(\bar{C}_{ij}, \tau^2)$$

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- ▷ use expectation form
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- ▷ by the corollary

assumption

$$C'_{ij} \sim \mathcal{N}(\bar{C}_{ij}, \tau^2)$$

calculate θ by using w as:

$$\begin{aligned}\theta_{ij} &= \Phi_{\rho^2}(w_{ij} + \bar{C}_{ij}), \\ \bar{C}_{ij} &= \rho \cdot \Phi_1^{-1}\left(\Pr(X_i(t)=1 \mid X_j[t_\Delta]=0)\right).\end{aligned}$$

third step

estimate types of neurons consistent with data:

- excitatory neurons - positive connections only
- inhibitory neurons - negative connections only

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- excitatory neurons - positive connections only
- inhibitory neurons - negative connections only

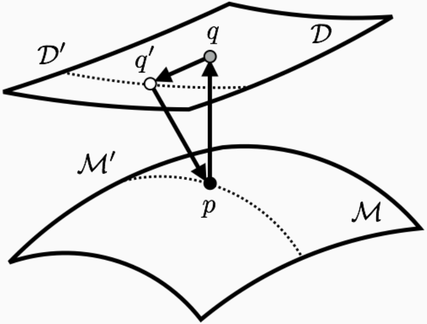
treated as hidden variables $\mathbf{z} \in \{0, 1\}^{N}$:

$$\Pr(\text{Data} \mid W, \mathbf{z}) \Leftrightarrow \Pr(\mathbf{z} \mid \text{Data}, W)$$

third step

estimate types of neurons consistent with data:

- excitatory neurons - positive connections only
- inhibitory neurons - negative connections only



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$$\Pr(\mathsf{Data} \mid \mathsf{W}, \mathbf{z}) \Leftrightarrow \Pr(\mathbf{z} \mid \mathsf{Data}, \mathsf{W})$$

use em algorithm (Amari 1995)
with approximations:

- factorial model in data manifold
- Gibbs sampling

Proposed Algorithm:

Input: $\Lambda, \bar{C}, \mathbf{z}$

function ESTIMATEW($\Lambda, \bar{C}, \mathbf{z}$)

  Initialization: $\Theta^{(1)} \leftarrow [0,1]^{N\times N}$, $\Lambda^{(1)} \leftarrow \Lambda$

  for $\tau \leftarrow 1, T$ **do**

    $W^{(\tau+1)} \leftarrow \Lambda^{(\tau)}(I - \Theta^{(\tau)})$

    for $i \leftarrow 1, N$ **do**

      for $j \leftarrow 1, N$ **do**

$$[\hat{W}(\mathbf{z})^{(\tau+1)}]_{ij} \leftarrow \begin{cases} z_j[W^{(\tau+1)}]_{ij}, & [W^{(\tau+1)}]_{ij} > 0 \\ (1 - z_j)[W^{(\tau+1)}]_{ij}, & [W^{(\tau+1)}]_{ij} < 0 \end{cases}$$

      end for

    end for

    $\left[\Theta^{(\tau+1)}\right]_{ij} \leftarrow \Phi_1\left([\hat{W}(\mathbf{z})^{(\tau+1)}]_{ij} + \bar{C}_{ij}\right)$

    $\mathrm{diag}(\boldsymbol{\Theta}^{(\tau+1)}) \leftarrow 0$ ▷ update diagonal elements

    $\Lambda^{(\tau+1)} \leftarrow \Lambda^{(\tau)}$

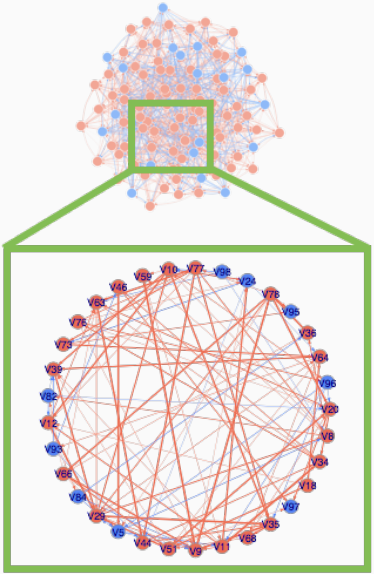
    $\mathrm{diag}(\Lambda^{(\tau+1)}) \leftarrow \mathrm{diag}(\Lambda^{(\tau)}\Theta^{(\tau+1)})$ ▷ update diagonal elements

  end for

end function

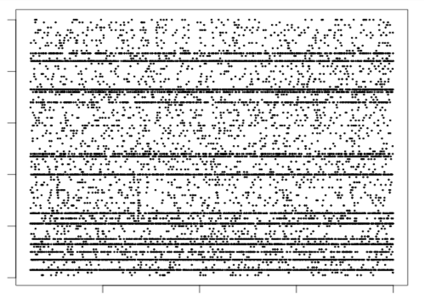
Output: $\hat{W}(\mathbf{z})$

Numerical Examples

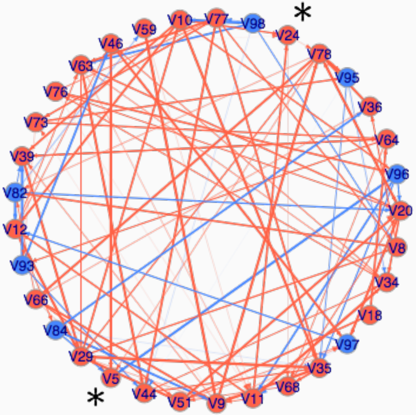


Izhikevich's neuron model (Izhikevich 2003)

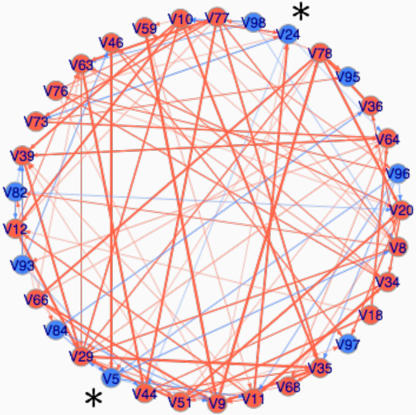
- $\mathsf{N} = 33$ out of 100 neurons
- excitatory:inhibitory = 80%:20%
- $w_{ij} \sim \texttt{Unif}[-10, 10]$
- $\#\{w_{\cdot j}\} \leq 10$



true



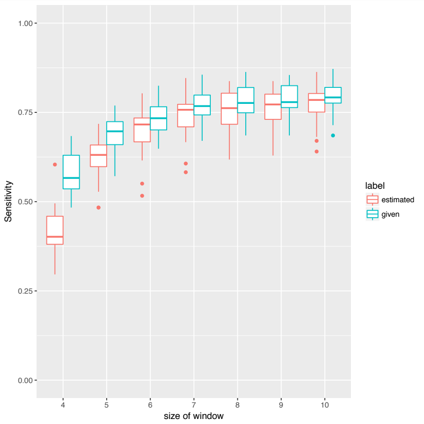
estimated



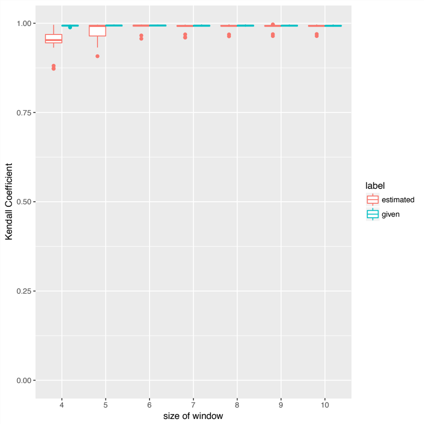
remarks

- estimation is scale indeterminate
- inhibitory connections are difficult to estimate

sensitivity



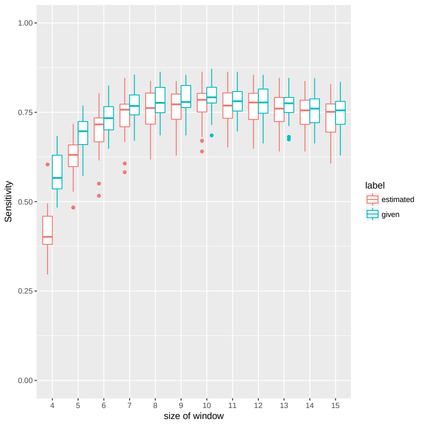
Kendall coefficient



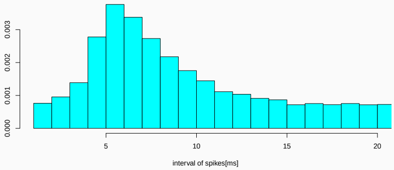
remarks

- estimation accuracy gets better if neuron types are given
- order of weights is estimated with sufficient accuracy

sensitivity



spike interval

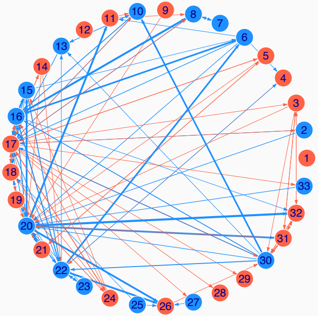


remark

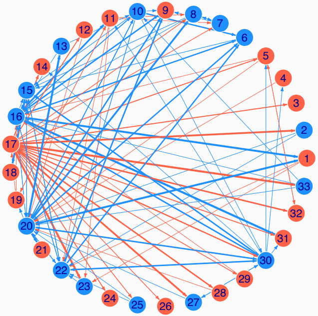
- sensitivity is affected by choice of correlation interval memory trace replay: (Wilson and McNaughton 1994; Tatsuno, Lipa, and McNaughton 2006)

- purpose: examine the hyposesis “the replay of activity patterns during sleep plays an important role in the consolidation process of memory”
- measurements:
  - pre-task: activity of control
  - task: activity in learning stage
  - post-task: activity in non-REM stage

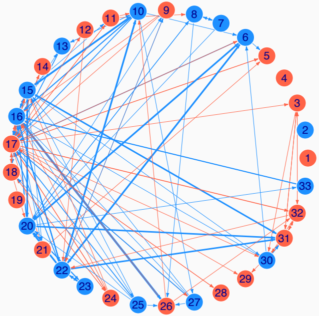
pre-task



task



post-task



remarks

- some connections changed at task period are retained at post-task period (e.g. 8,11,12,20)
- result should be discussed from the viewpoint of biology

Concluding Remarks

we consider an approach to solve the following problems:

- pseudo correlation caused by higher-order effect
- influence from unobserved neurons
- directional excitatory/inhibitory connections

possible extension would be:

- estimating the number of connections
- estimating activation functions of individual neurons
- applying other real-world data

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