



Reconstruction of Network Connectivity from Observations

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Part I: continuous time signals, appropriate for data estimation

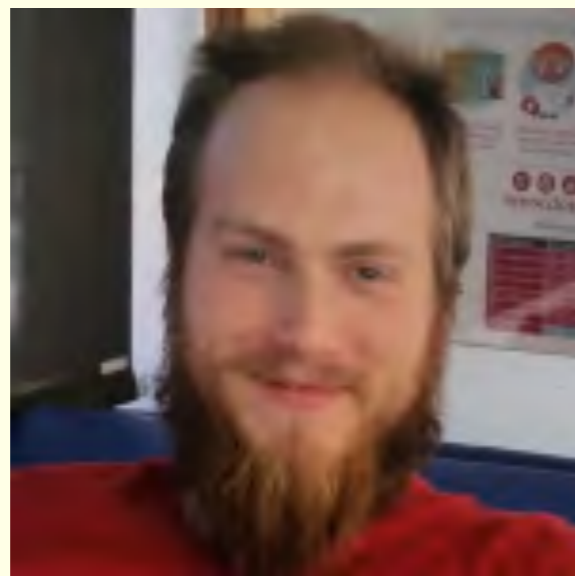
Björn Kralemann



Arkady Pikovsky

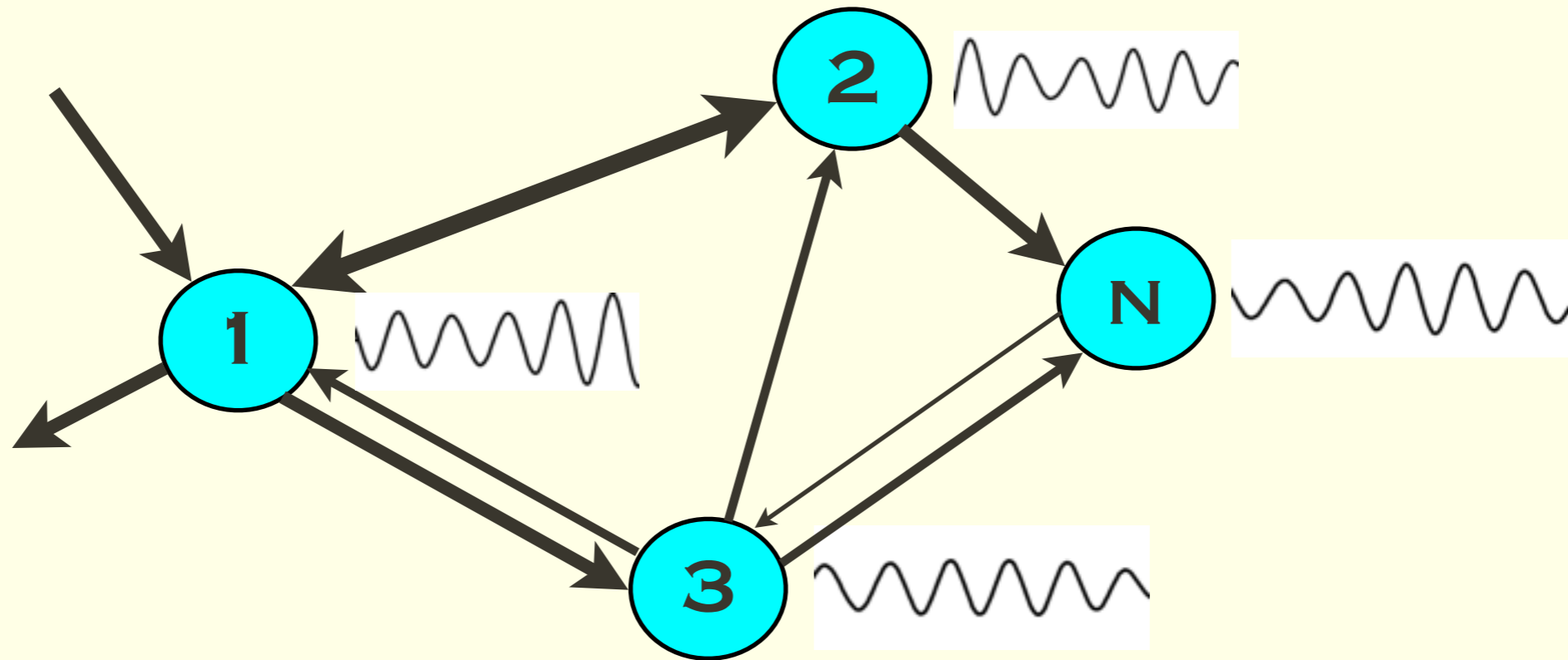


Part II: spike data (point processes)



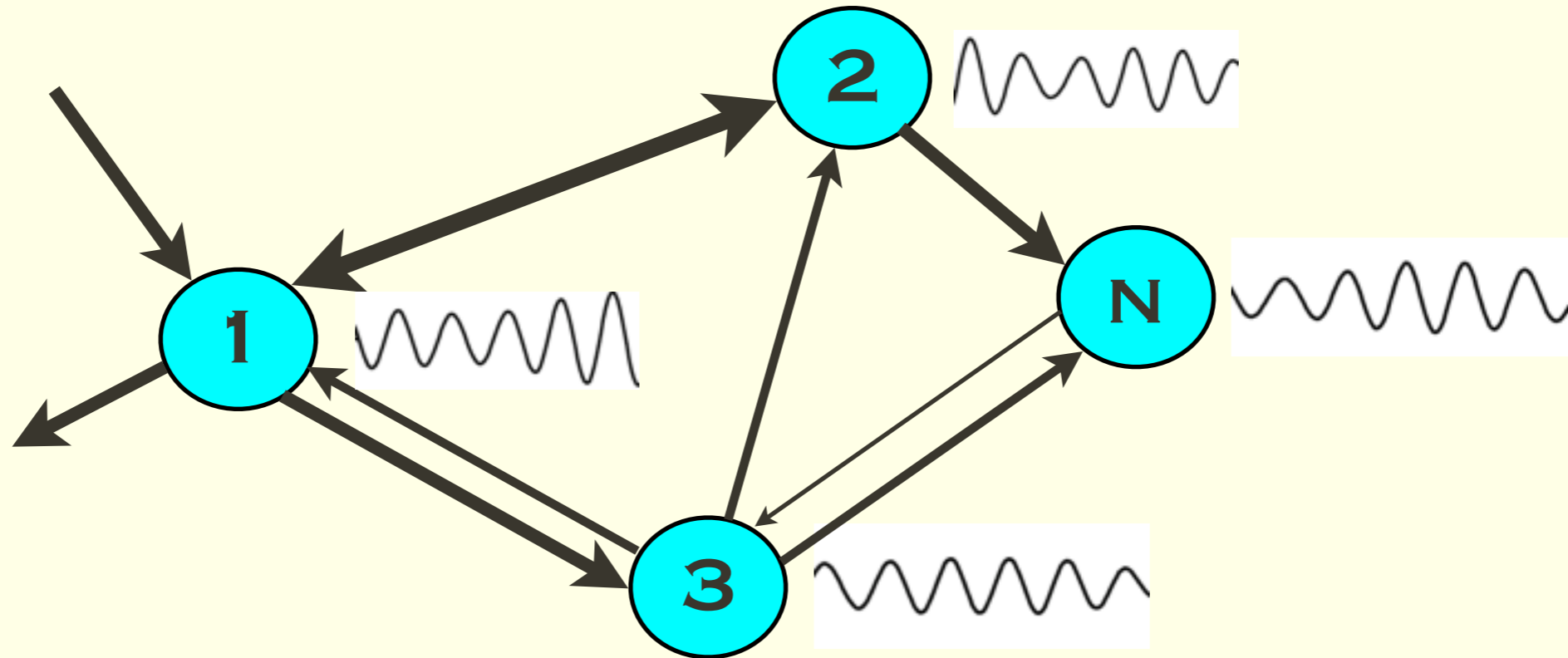
Rok Cestnik

Formulation of the problem



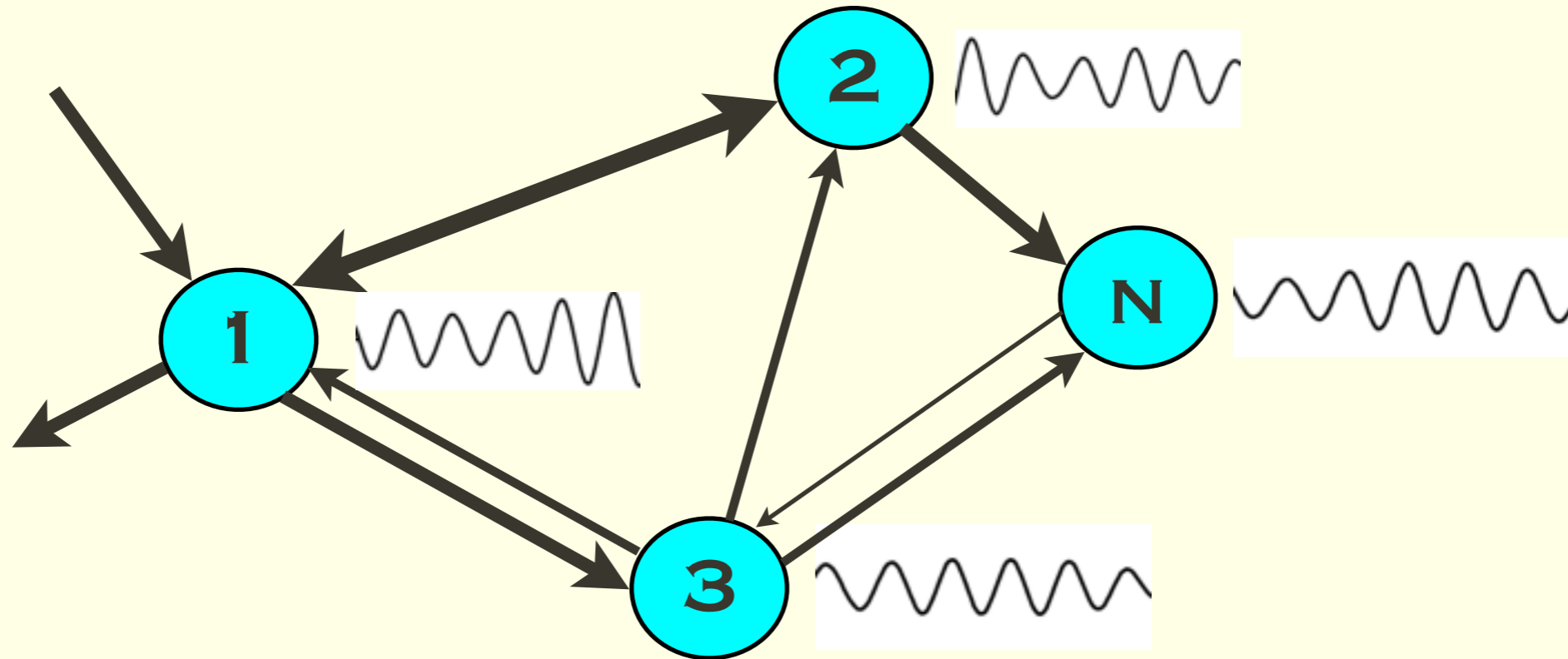
- **Data:** we have oscillatory signals coming from several *weakly coupled self-sustained oscillators*
- **Our goal:** to say as much as possible about the systems and their interaction
- **Particular problem:** to reconstruct *directional connectivity*
- What kind of connectivity do we detect?
 - this will be discussed in detail later

Formulation of the problem: assumptions



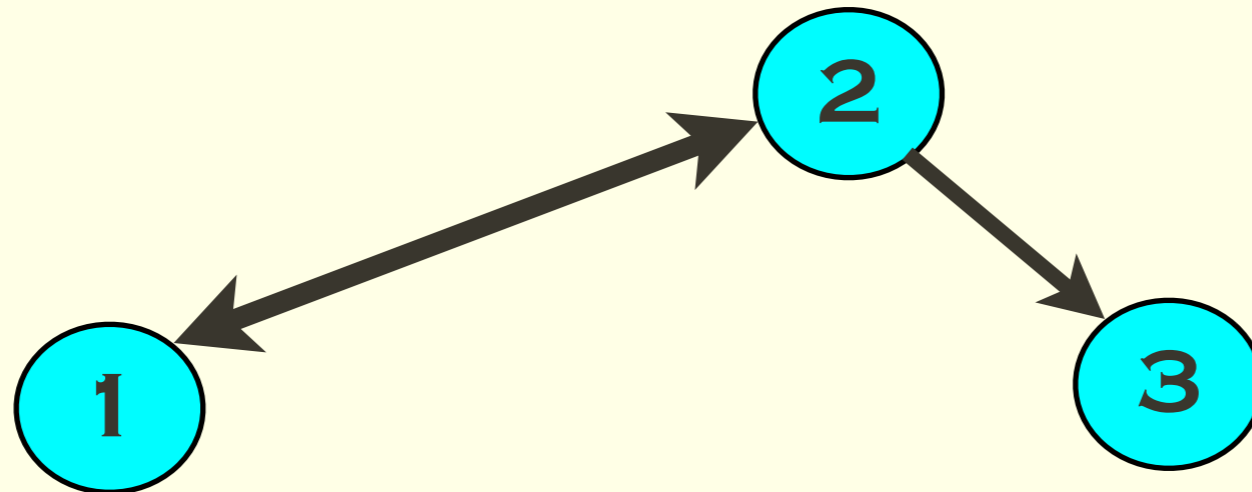
- **Assumption 1:** all units are observed
- **Assumption 2:** the units are **self-sustained** oscillators
- **Assumption 3:** the interaction between the units is not too strong
- **Assumption 4:** signals are good for **estimation of phases**

Connectivity of an Oscillator Network



- **Data:** we have oscillatory signals coming from several *weakly coupled self-sustained oscillators*
- **Problem:** to reconstruct *directional connectivity*
- What kind of connectivity do we detect?
Structural vs effective vs functional connectivity

Structural connectivity



- Real physical connection: resistor, optical fiber...
Biological system: **anatomical connection**, e.g., via synapses
- Mathematically, e.g., for the 2nd node:

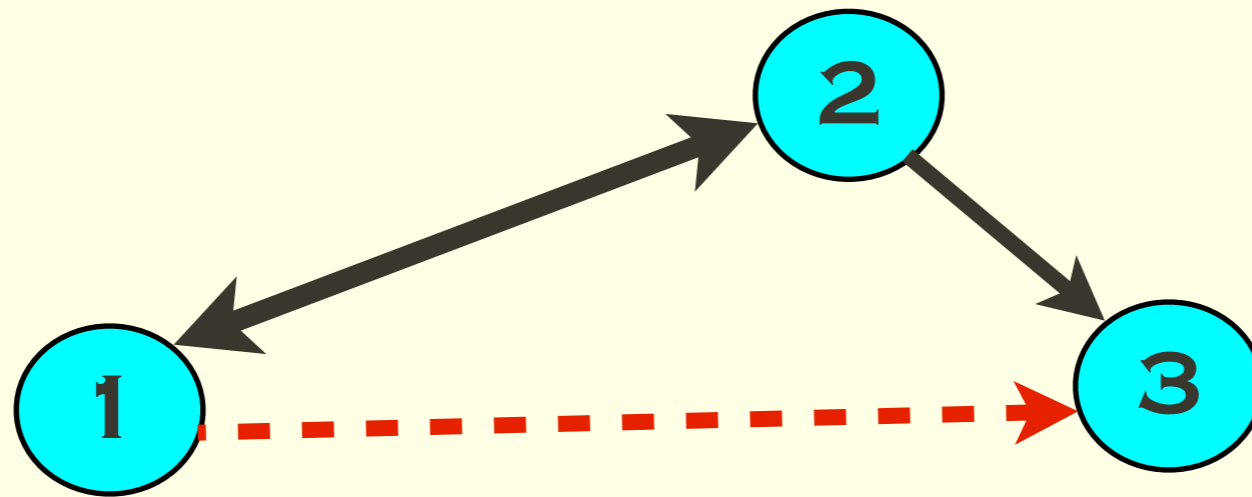
$$\dot{\mathbf{x}}_2 = \mathbf{G}_2(\mathbf{x}_2) + \varepsilon \mathbf{H}_2(\mathbf{x}_2, \mathbf{x}_1)$$

autonomous dynamics

coupling function

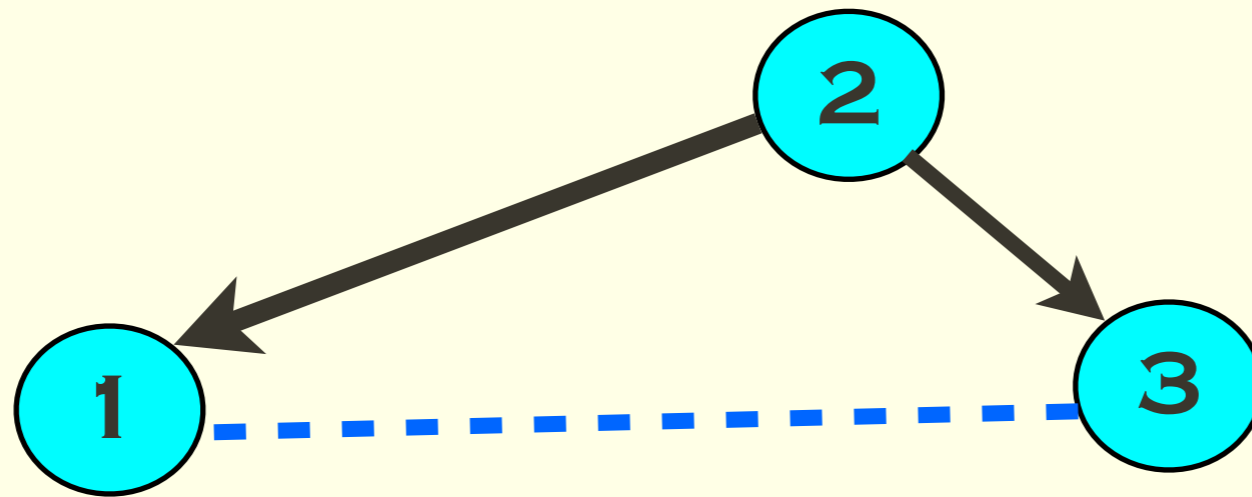
Remark: “coupling” = “physical connection”

Effective phase connectivity



- Nodes 1 and 3 are not physically connected, but phase dynamics of node 3 may depend on the state of node 1. Then, nodes 1, 3 are *effectively connected* (unidirectionally)
- Structural connectivity \neq effective phase connectivity

Functional connectivity



- Nodes 1 and 3 are not physically connected, but they may be correlated or synchronized due to the common drive 2
 - ⇒ Nodes 1, 3 are functionally connected
- Notice: (1) functional connectivity is not directed
 - (2) functional connectivity is only loosely related to the structural and effective ones

We quantify the

effective phase connectivity

by reconstructing the model of phase

dynamics from data

- Namely, we perform:
- Protophase estimation
 - Protophase-to-phase transformation
 - Reconstruction of coupling functions
 - Analysis of coupling functions

Network of coupled oscillators

- Individual oscillator: $\dot{\mathbf{x}}_k = \mathbf{G}_k(\mathbf{x}_k)$
 - limit cycle, parameterized by phase φ_k
 - phase grows linearly with time: $\dot{\varphi}_k = \omega_k = \text{const}$
- A network of N coupled oscillators
$$\dot{\mathbf{x}}_k = \mathbf{G}_k(\mathbf{x}_k) + \varepsilon \mathbf{H}_k(\mathbf{x}_1, \mathbf{x}_2, \dots)$$
- If \mathbf{x}_l enters the equation for \mathbf{x}_k then there is a direct structural connection $l \rightarrow k$
- If $\mathbf{H}_k = \sum_{j \neq k} \mathbf{H}_{kj}(\mathbf{x}_k, \mathbf{x}_j)$ then coupling is pairwise
(We consider only this case)
- If there are terms $\mathbf{H}_{kjl}(\mathbf{x}_k, \mathbf{x}_j, \mathbf{x}_l)$: cross-coupling

Weak coupling: Phase description

- Weak coupling, no synchrony: motion on the *N-torus* in the phase space of the full system

- This motion can be parameterized by N phases:

$$\dot{\varphi}_k = \omega_k + q_k(\varphi_1, \varphi_2, \dots), \quad k = 1, \dots, N$$

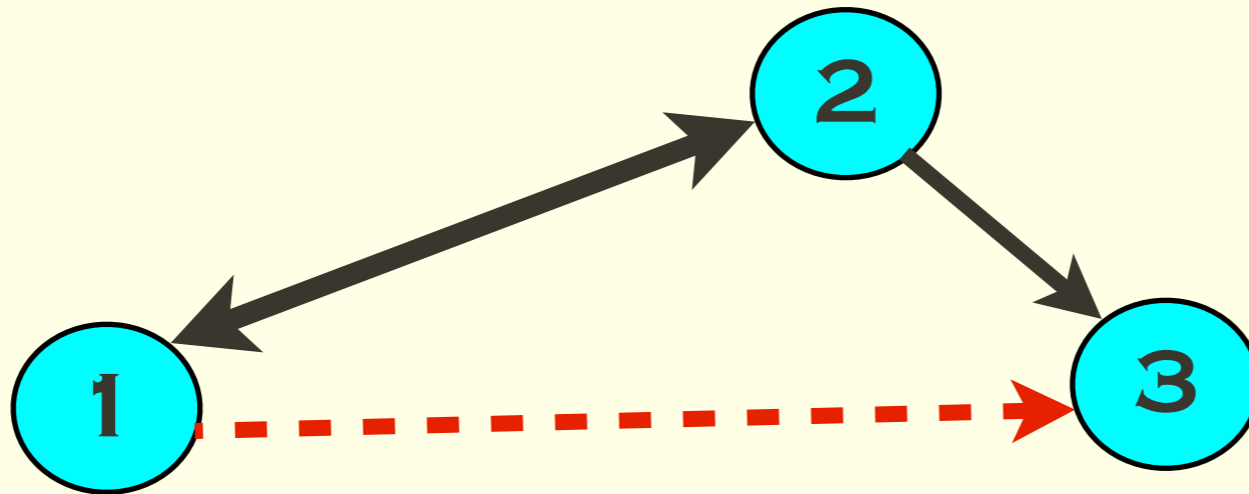
- New coupling functions q_k can be obtained by a perturbative reduction (Kuramoto 84):

$$q_k(\varphi_1, \varphi_2, \dots) = \varepsilon q_k^{(1)}(\varphi_1, \varphi_2, \dots) + \varepsilon^2 q_k^{(2)}(\varphi_1, \varphi_2, \dots) + \dots$$

- Pairwise coupling in the full system:

- first-order approximation: pairwise terms like $\varepsilon q_{kl}^{(1)}(\varphi_k, \varphi_l)$
- high-order approximation: *terms, depending on many phases*, not only on the phases of directly coupled nodes

Effective phase connectivity



- Nodes 1 and 3 are not physically connected, but phase dynamics of node 3 may depend on the state of node 1. Then, nodes 1, 3 are *effectively connected* (unidirectionally)

$$\dot{\varphi}_3 = \omega_3 + \varepsilon q_3^{(1)}(\varphi_2, \varphi_3) + \varepsilon^2 q_3^{(2)}(\varphi_1, \varphi_2, \varphi_3)$$

- Structural connectivity \neq effective phase connectivity

There is no effective phase connection $3 \rightarrow 1$!

Coupling functions and quantification of interaction

We reconstruct the coupling functions in terms of Fourier coefficients, using LMS fit:

$$\begin{aligned}\frac{d\varphi_k}{dt} &= \omega_k + q_k(\varphi_1, \varphi_2, \dots, \varphi_N) \\ &= \sum_{l_1, \dots, l_N} \mathcal{F}_{l_1, \dots, l_N}^{(k)} \exp(il_1\varphi_1 + il_2\varphi_2 + \dots + l_N\varphi_N)\end{aligned}$$

Norm of the coupling function q_k quantifies effect of the rest of the network on oscillator k

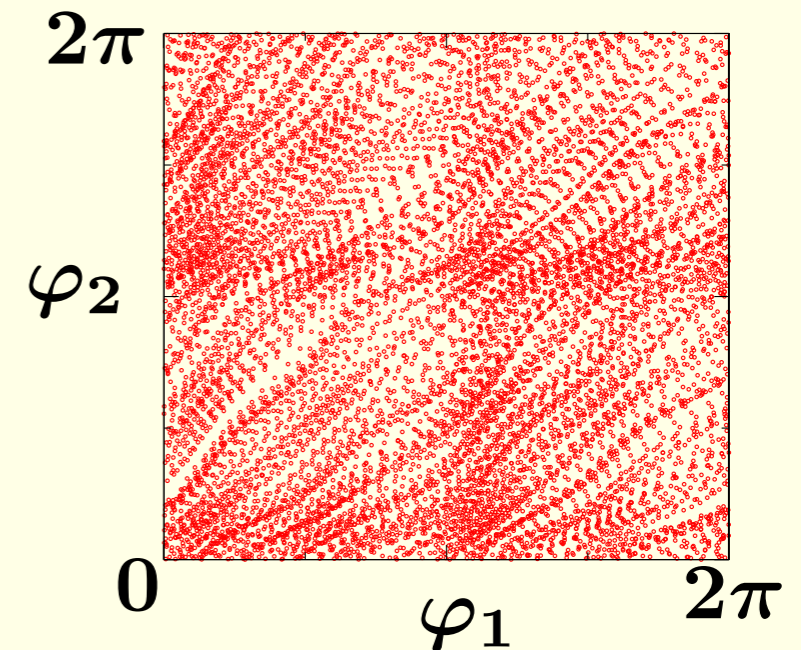
Action of particular oscillator $j \rightarrow k$

Partial norm $\mathcal{N}_{k \leftarrow j}^2 = \sum_{l_k, l_j \neq 0} \left| \mathcal{F}_{0, \dots, l_k, 0, \dots, l_j, 0, \dots}^{(k)} \right|^2$

Numerical problem

- Two coupled oscillators: to reconstruct the coupling function we need enough data points to cover the square

$$0 < \varphi_{1,2} \leq 2\pi$$



- Three coupled oscillators: we need enough data points to cover the cube $0 < \varphi_{1,2,3} \leq 2\pi$
- N coupled oscillators: we need enough data points to cover the hypercube.... **It is not feasible!**

Typically: pairwise analysis. We suggest an analysis by triplets.

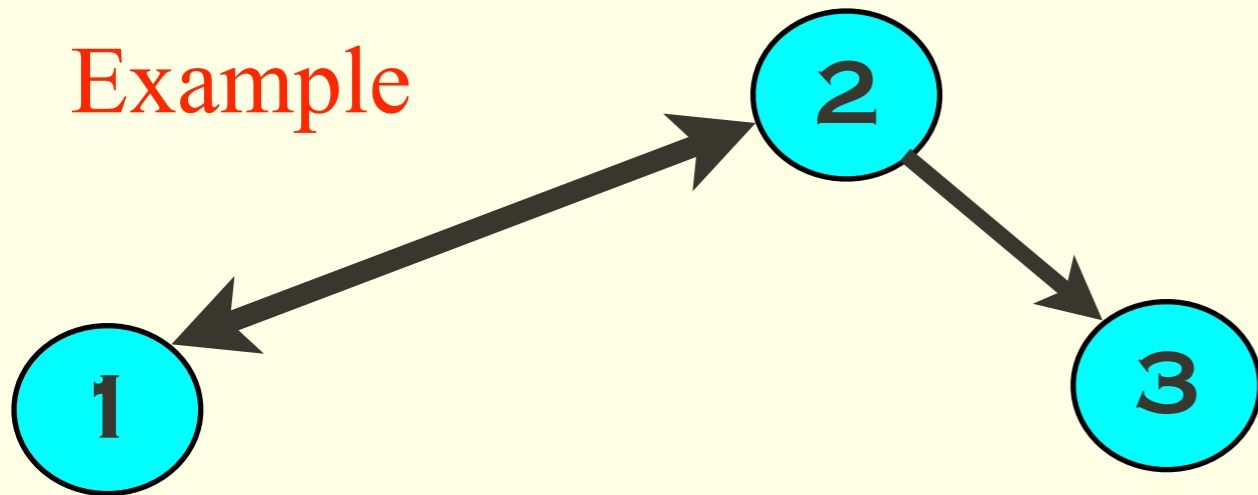
Partial phase dynamics

Pairwise analysis: we fit the function of two phases, ignoring all others:

$$\dot{\varphi}_k = \omega_k + q_{kj}(\varphi_j, \varphi_k)$$

Norm $\mathcal{P}_{k \leftarrow j} = \|q_{kj}\|$ quantifies link $k \leftarrow j$

Example



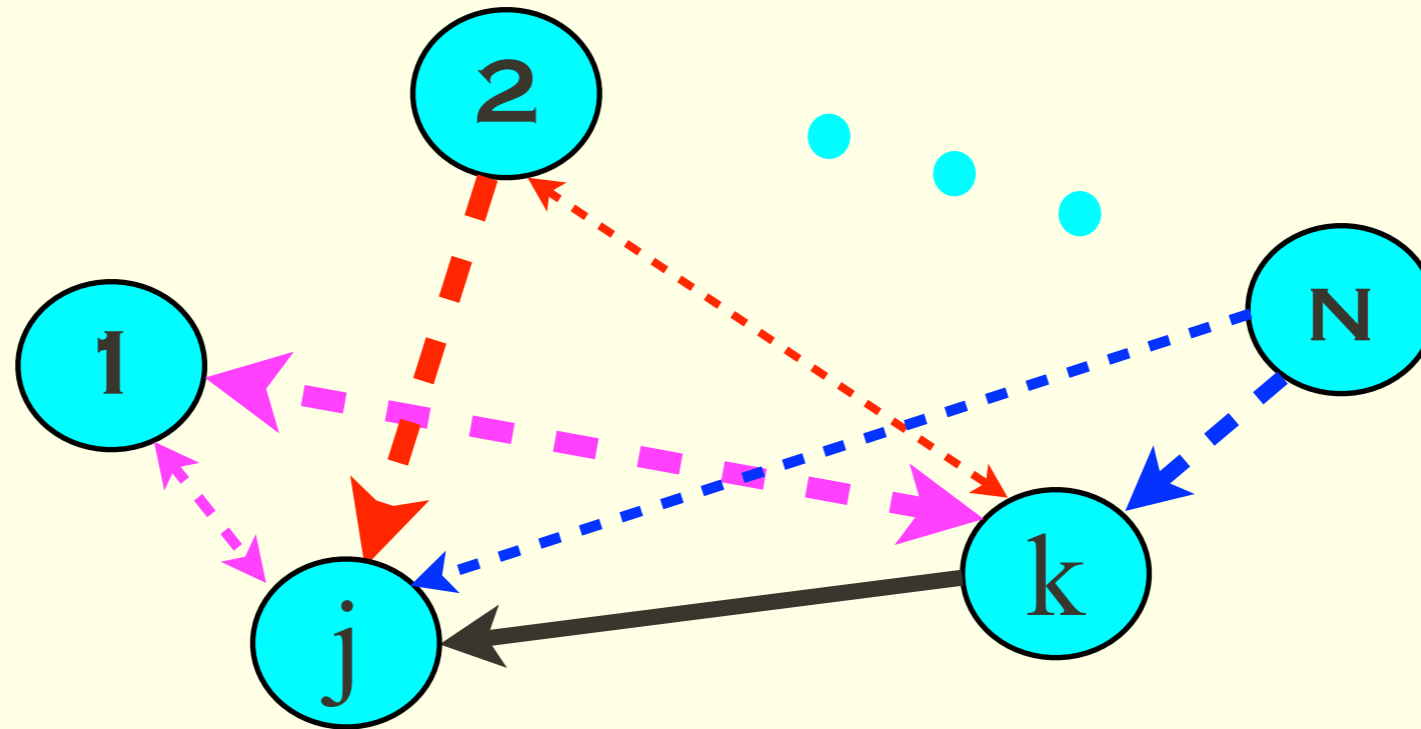
Pairwise analysis yields spurious connection $1 \rightarrow 3$

Triplet analysis yields correct connectivity (Kralemann et al 2011)

What to do for networks with $N > 3$?

Triplet analysis of networks with $N > 3$

We reconstruct $\dot{\varphi}_j = \omega_j + q_{jkm}(\varphi_j, \varphi_k, \varphi_m)$ for all m

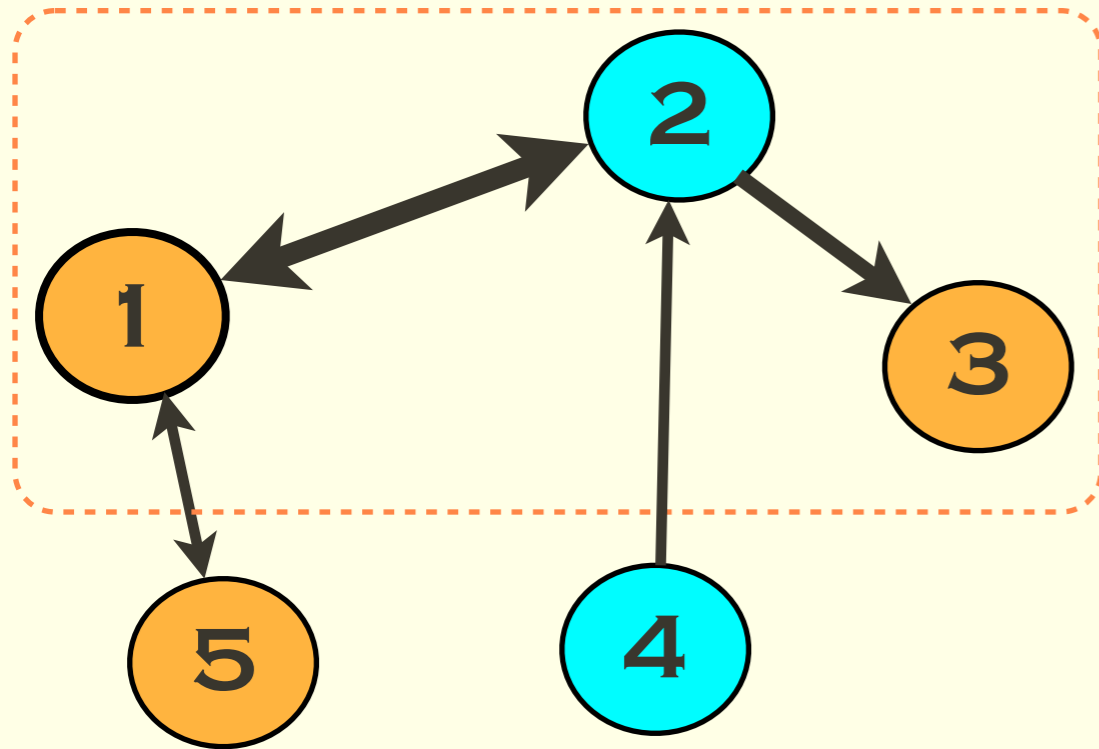


From each triplet we obtain partial norm:

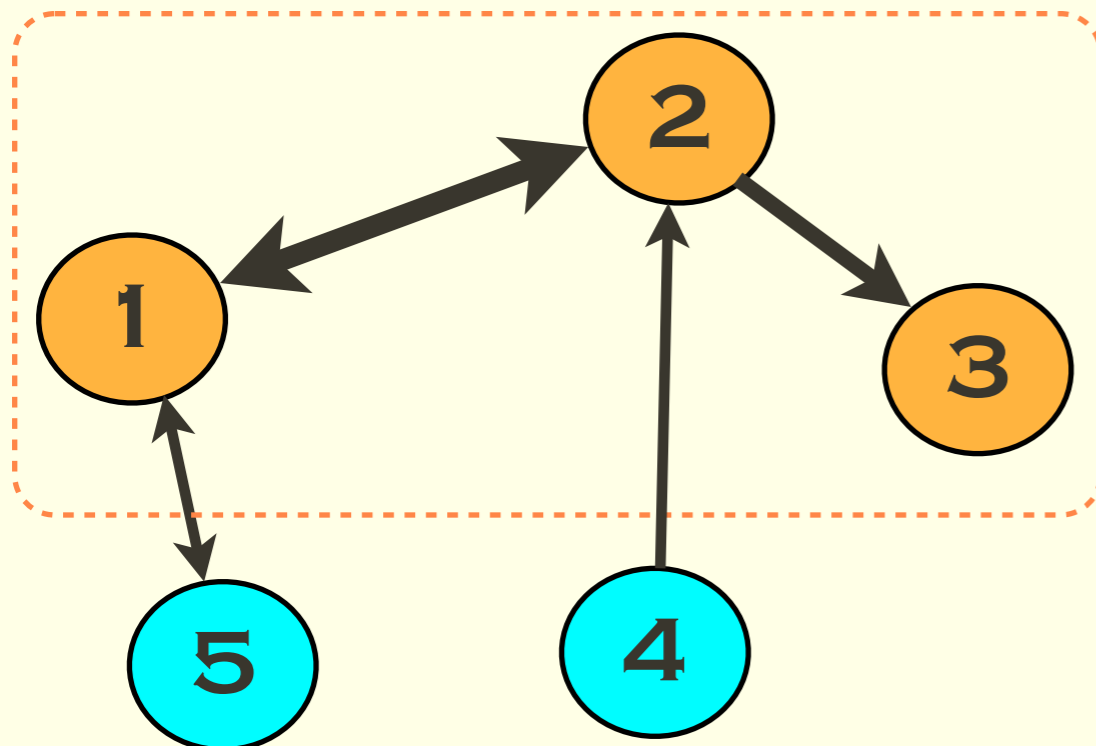
$$\tilde{\mathcal{T}}_{j \leftarrow k}^2(m) = \sum_{l_j, l_k \neq 0} \left| \mathcal{F}_{l_j, l_k, 0}^{(j)} \right|^2$$

We suggest to take $\mathcal{T}_{j \leftarrow k} = \min_m \tilde{\mathcal{T}}_{j \leftarrow k}(m)$ as the final triplet-based measure of the binary effective connectivity

Triplet analysis of networks with $N > 3$



Triplet $\{1,3,5\}$ yields spuriously large term $1 \rightarrow 3$, because φ_1, φ_3 are correlated due to node 2



Triplet $\{1,2,3\}$ correctly explains correlation of φ_1, φ_3 and yields a small value for the link $1 \rightarrow 3$

Example: three van der Pol oscillators

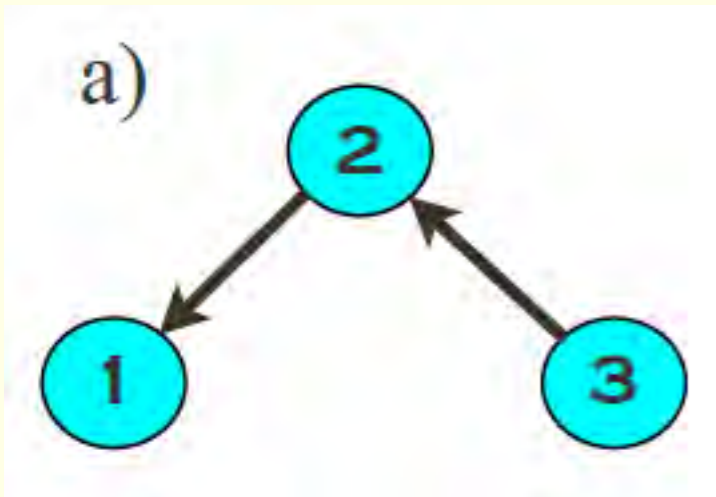
$$\begin{aligned}\ddot{x}_1 - \mu(1 - x_1^2)\dot{x}_1 + \omega_1^2 x_1 &= \varepsilon[\sigma_{12}(x_2 + \dot{x}_2) + \sigma_{13}(x_3 + \dot{x}_3)] , \\ \ddot{x}_2 - \mu(1 - x_2^2)\dot{x}_2 + \omega_2^2 x_2 &= \varepsilon[\sigma_{21}(x_1 + \dot{x}_1) + \sigma_{23}(x_3 + \dot{x}_3)] , \\ \ddot{x}_3 - \mu(1 - x_3^2)\dot{x}_3 + \omega_3^2 x_3 &= \varepsilon[\sigma_{31}(x_1 + \dot{x}_1) + \sigma_{32}(x_2 + \dot{x}_2)] .\end{aligned}$$

Parameters:

$$\begin{aligned}\varepsilon &= 0.2 & \mu &= 0.5 \\ \omega_1 &= 1 & \omega_2 &= 1.3247 & \omega_3 &= 1.75483\end{aligned}$$

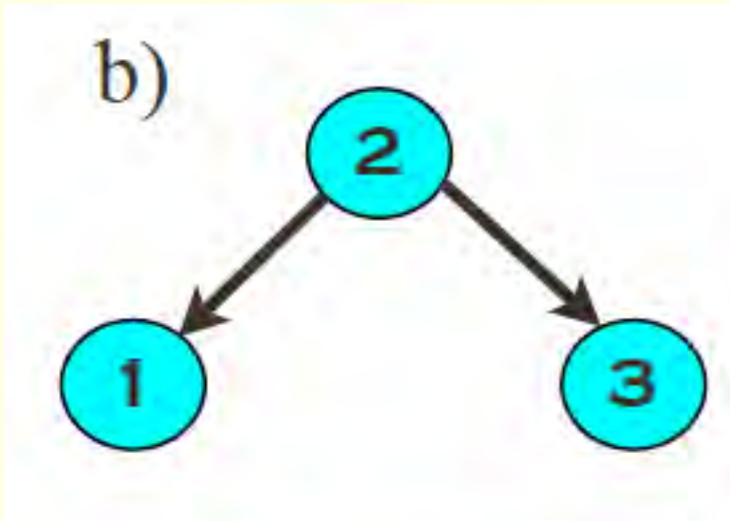
Connectivity matrix: $\sigma_{i,j} = 0$ or 1

Example, $N=3$, results



(a)	Osc_1	Osc_2	Osc_3
Osc_1		0.103 , 0.104	0.018 , 0.024
Osc_2	0.002 , 0.009		0.095 , 0.095
Osc_3	0.001 , 0.001	0.001 , 0.001	

$\mathcal{N}_{3 \leftarrow 2}, \mathcal{P}_{3 \leftarrow 2}$



(b)	Osc_1	Osc_2	Osc_3
Osc_1		0.113 , 0.113	0.003 , 0.016
Osc_2	0.001 , 0.001		0.001 , 0.001
Osc_3	0.005 , 0.020	0.092 , 0.092	

$\mathcal{N}_{3 \leftarrow 1}, \mathcal{P}_{3 \leftarrow 1}$

Remark: here $\mathcal{N}_{3 \leftarrow 2} = \mathcal{T}_{3 \leftarrow 2}$

Random oscillator network, $N=5$

$$\ddot{x}_k - \mu(1 - x_k^2)\dot{x}_k + \omega_k^2 x_k = \varepsilon \sum_l \sigma_{kl} (x_l \cos \Theta_{kl} + \dot{x}_l \sin \Theta_{kl})$$

σ_{kl} : random asymmetric connection matrix of zeros and ones

Fixed number of incoming connections (two)

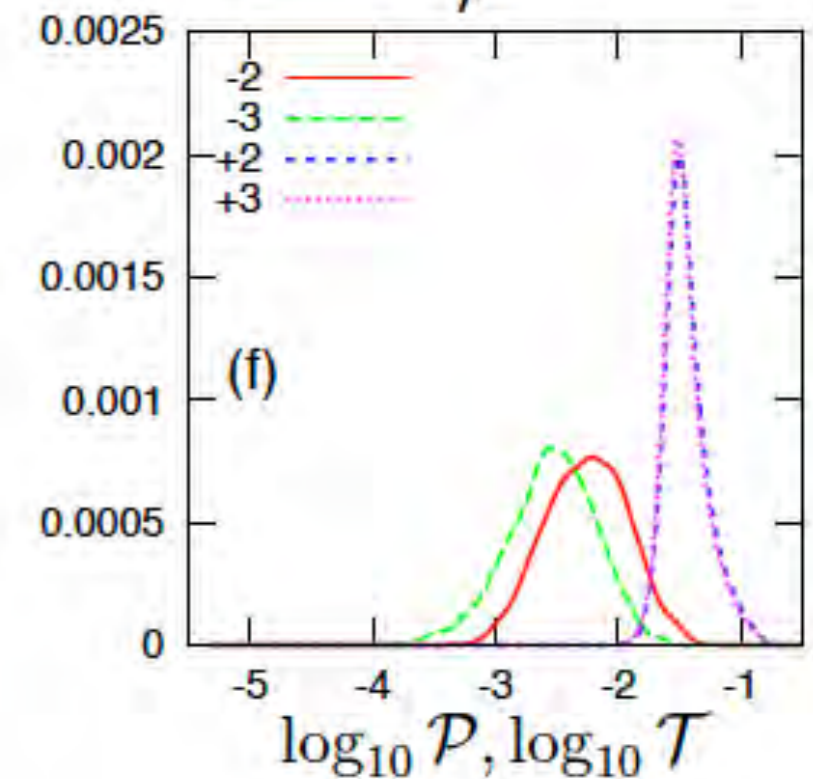
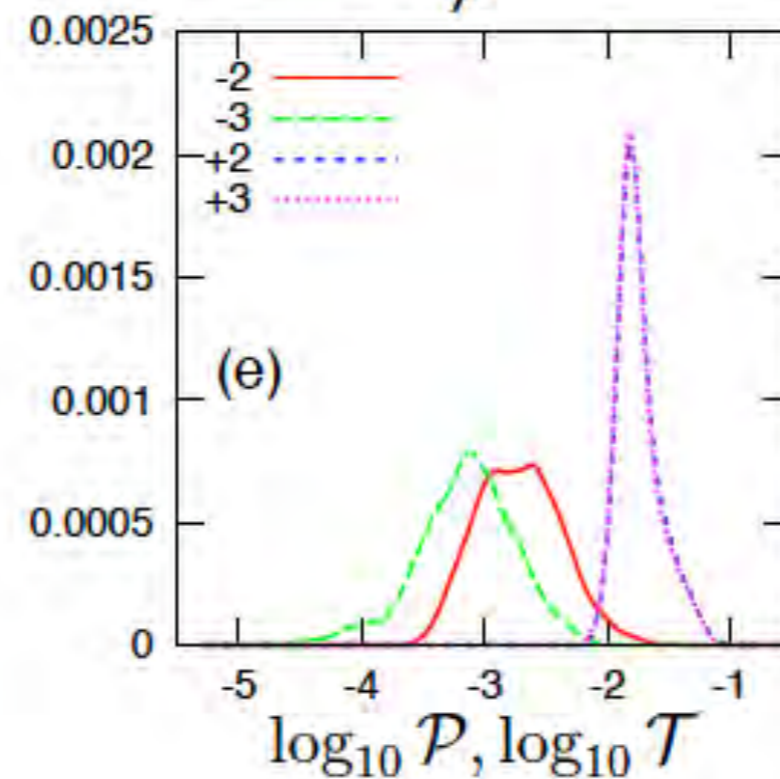
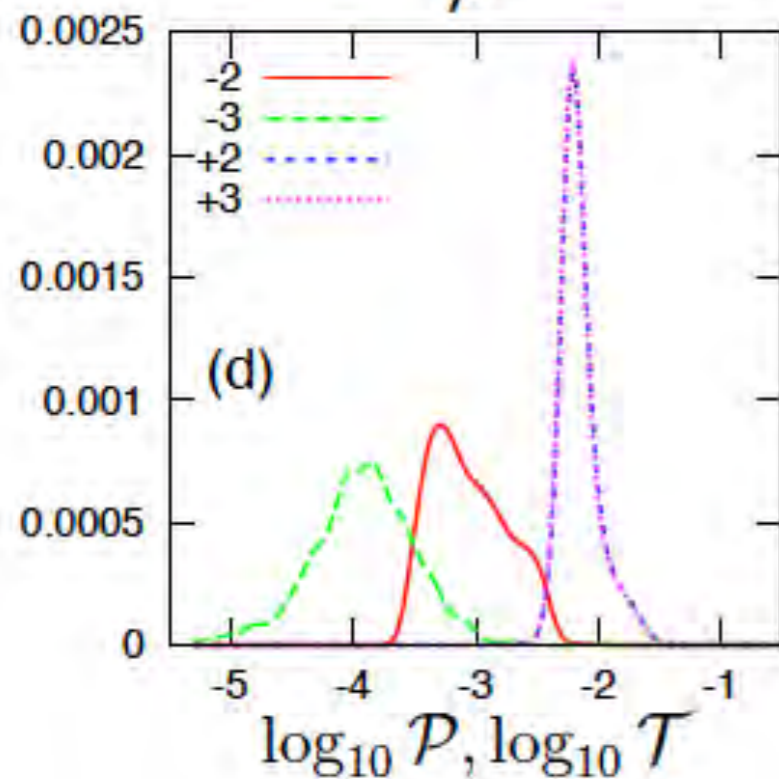
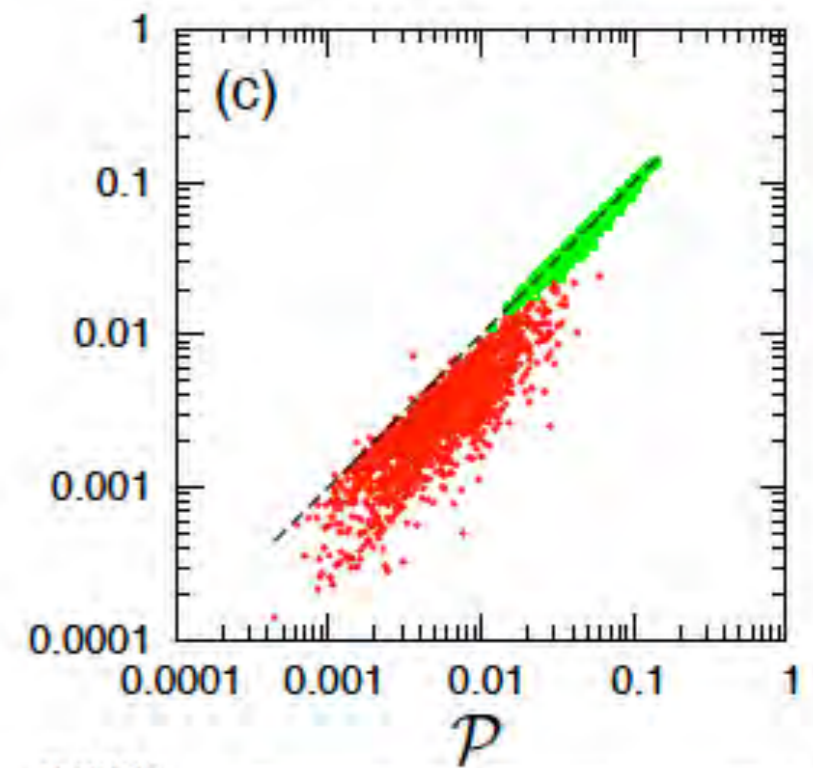
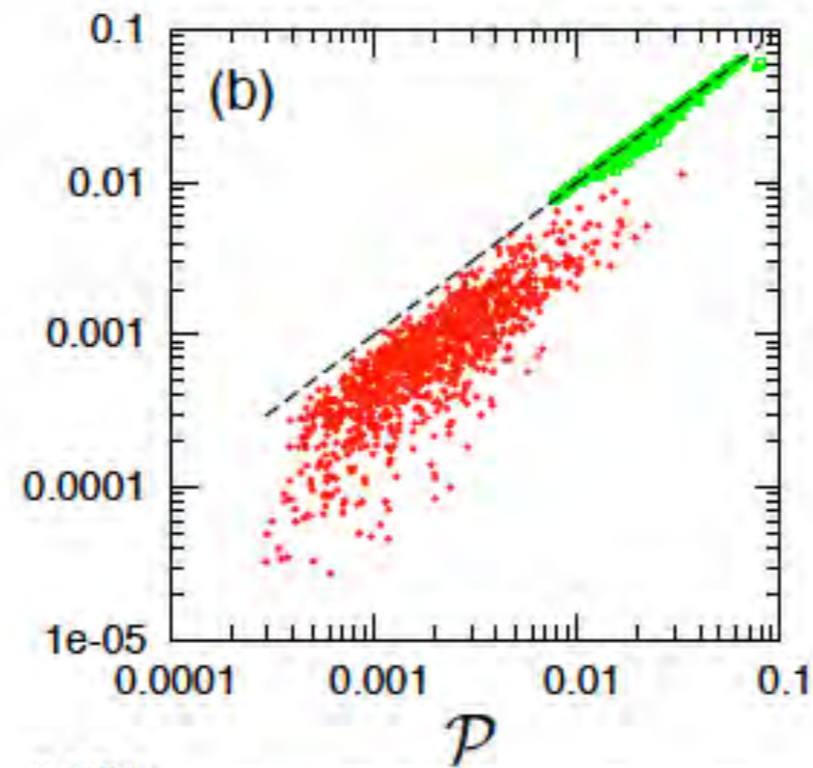
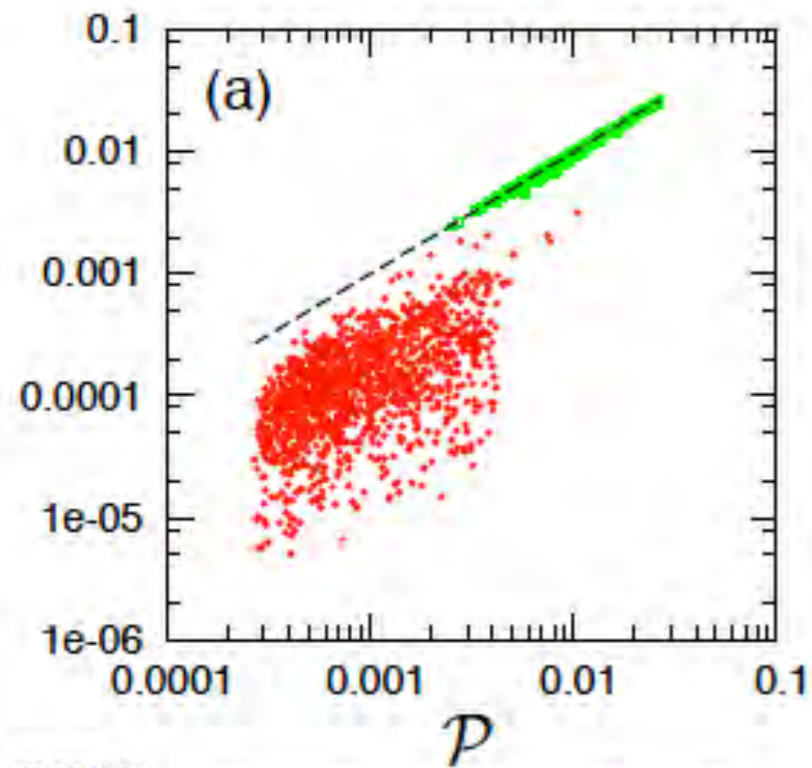
Frequencies are taken from a uniform distribution between 0.5 and 1.5

Θ_{kl} are taken from a uniform distribution between 0 and 2π

States with high degree of synchrony are excluded

Random oscillator network, $N=5$, results

Existing connections in **green**, non-existing connections in **red**



$$\varepsilon = 0.02$$

$$\varepsilon = 0.05$$

$$\varepsilon = 0.1$$

Larger networks?

CHAOS 26, 093106 (2016)



Distinguishing between direct and indirect directional couplings in large oscillator networks: Partial or non-partial phase analyses?

Thorsten Rings^{1,2,a)} and Klaus Lehnertz^{1,2,3,b)}

¹*Department of Epileptology, University of Bonn, Sigmund-Freud-Straße 25, 53105 Bonn, Germany*

²*Helmholtz Institute for Radiation and Nuclear Physics, University of Bonn, Nussallee 14–16, 53115 Bonn, Germany*

³*Interdisciplinary Center for Complex Systems, University of Bonn, Brühler Straße 7, 53119 Bonn, Germany*

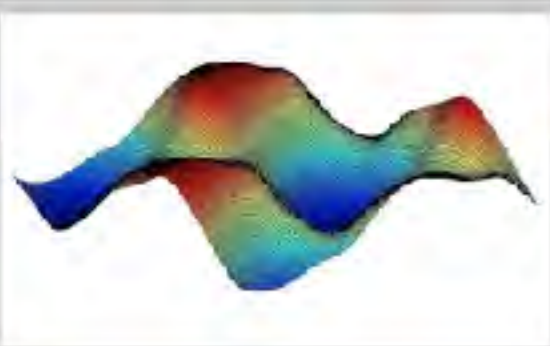
inherent to the recording technique. Our findings indicate that particularly in larger networks (number of nodes $\gg 10$), the partialized approach does not provide information about directional couplings extending the information gained with the evolution map approach. *Published by AIP Publishing.* [<http://dx.doi.org/10.1063/1.4962295>]

Conclusions

- Invariant reconstruction of phase equations for a network
- Characterization of directional couplings via partial norms
- Triplet analysis yields directed connectivity
- We detect effective phase connectivity, which is close but not equivalent to the structural connectivity

References

- B. Kralemann, A. Pikovsky, and M. Rosenblum, Chaos, 21, p. 025104, 2011
- B. Kralemann, A. Pikovsky, and M. Rosenblum, New J Phys, 16 085013, 2014



DAMOCO: Data Analysis with Models Of Coupled Oscillators

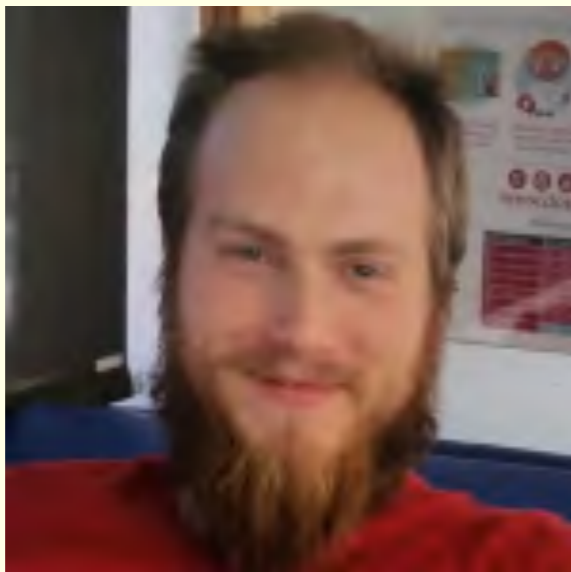
MATLAB Toolbox for multivariate time series analysis

Björn Kralemann, Michael Rosenblum, Arkady Pikovsky

Version 2.0 (2014)

**Software for data analysis can be downloaded from:
www.stat.physik.uni-potsdam.de/~mros/damoco2.html**

Reconstructing networks of pulse-coupled oscillators from spike trains



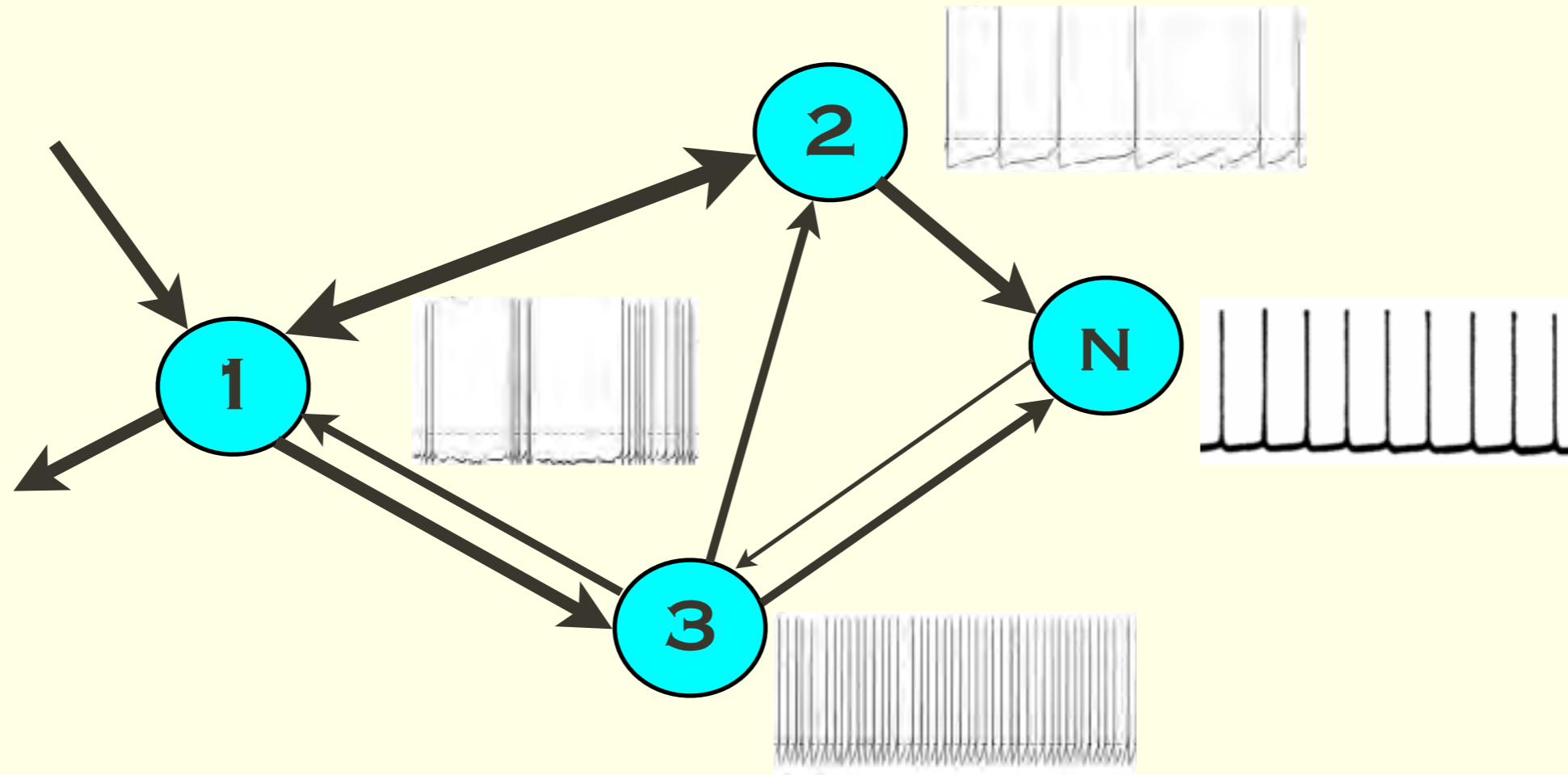
Rok Cestnik



**Complex Oscillatory Systems:
Modeling and Analysis**
Innovative Training Network
European Joint Doctorate

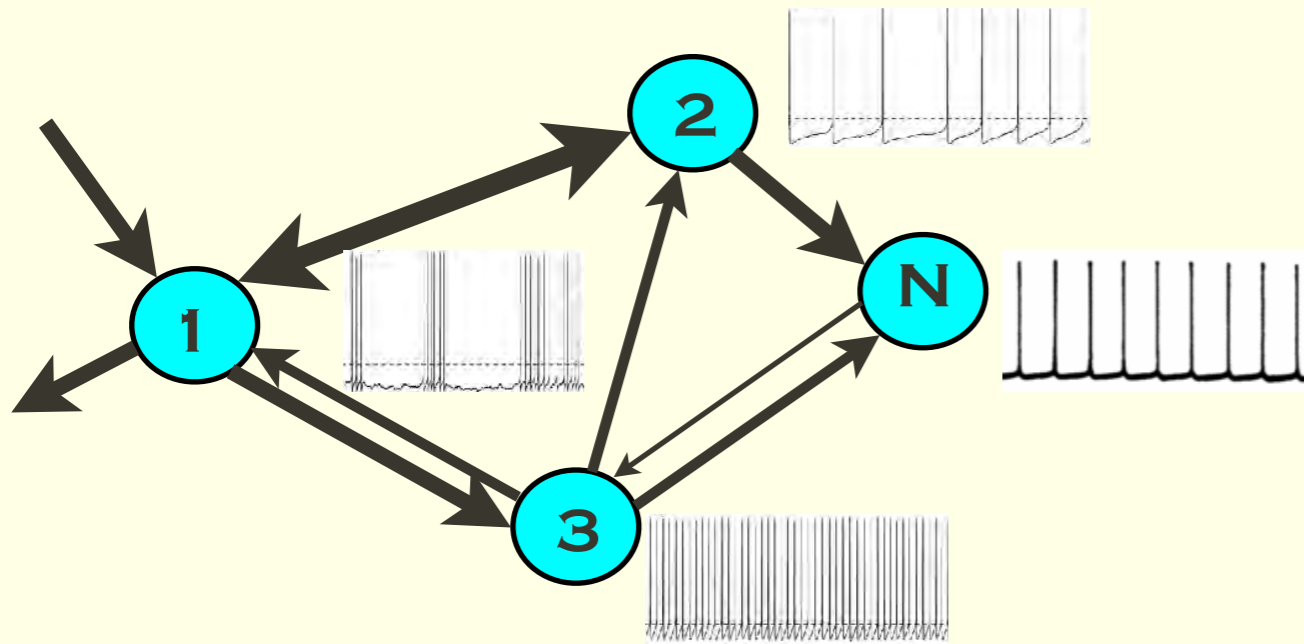


Formulation of the problem



The data we measure are like **sequences of spikes**

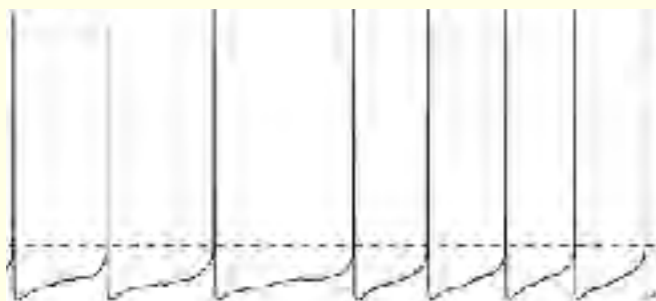
Formulation of the problem II



The data we measure are like **sequences of spikes**

→ we can reliably detect only times of spikes

→ we reduce the data to **point processes**



Assumptions about the network

- Weak interaction: phase description is justified
- PRC of a unit is the same for all incoming connections
PRCs of different units can differ!

- Coupling is bidirectional but generally asymmetric,

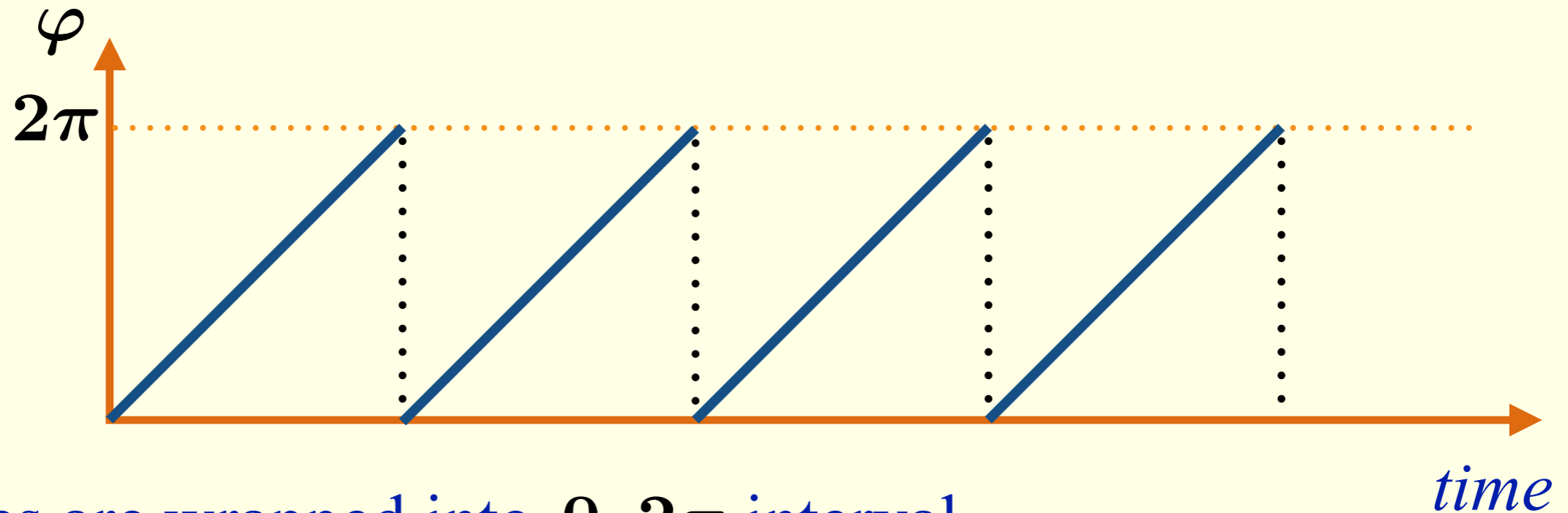
$$\varepsilon_{km} \neq \varepsilon_{mk}$$



strength of the link from m to k

A simple model: integrate-and-fire units

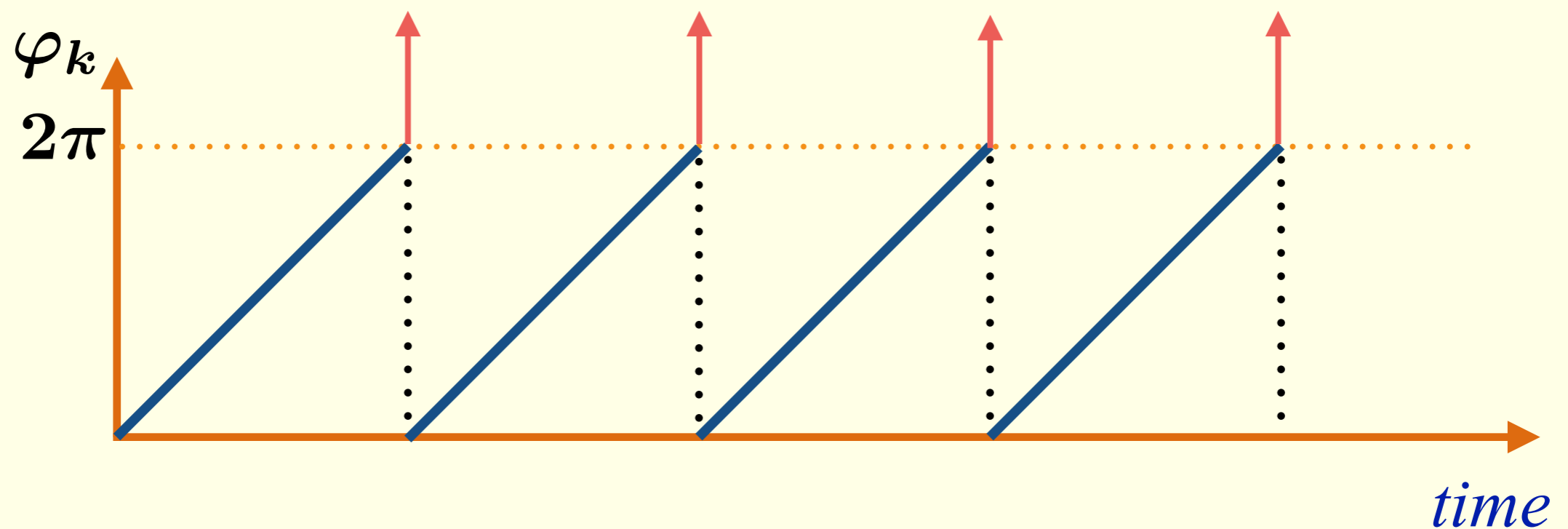
- Without interaction phases of all oscillators grow as $\varphi_k = \omega_k t$



phases are wrapped into $0, 2\pi$ interval

A simple model: integrate-and-fire units

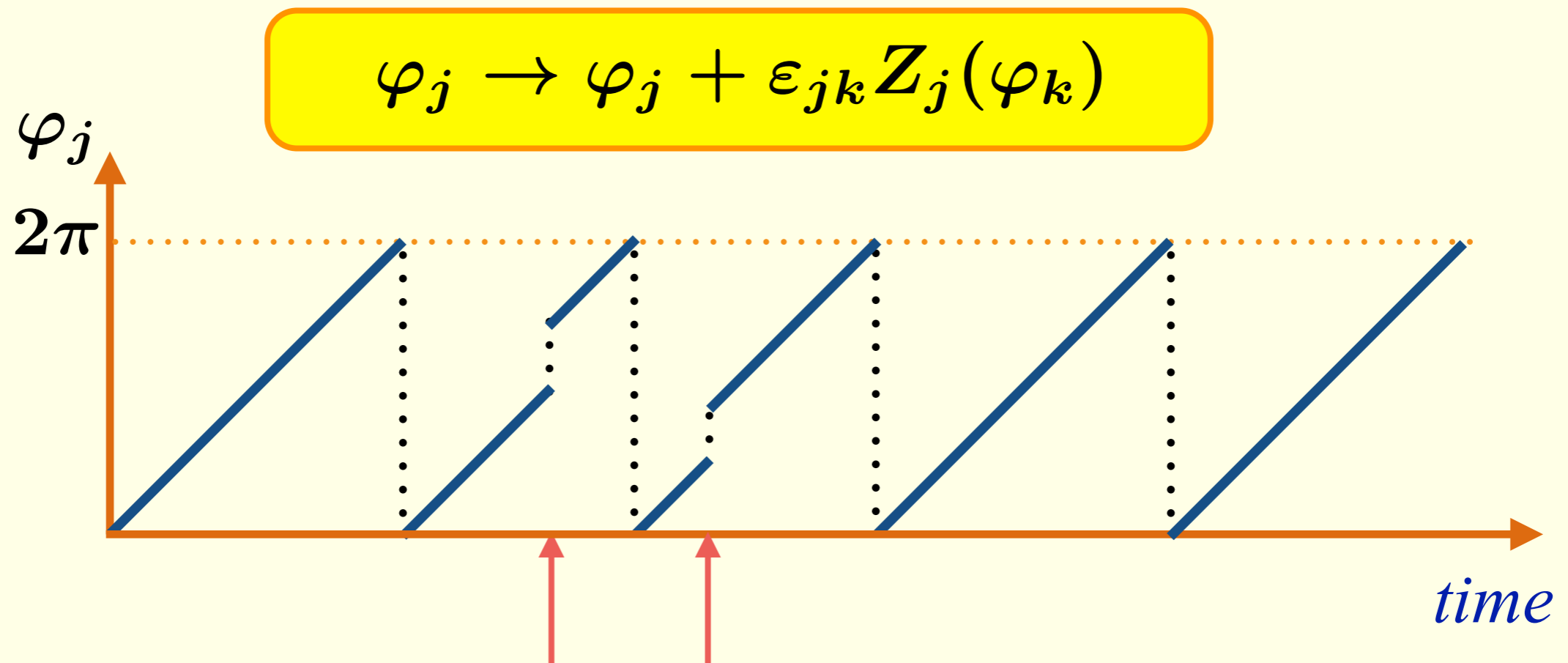
- Without interaction phases of all oscillators grow as $\varphi_k = \omega_k t$
- When phase of the oscillator k attains $\varphi_k = 2\pi$, it **issues a spike**



spikes affect all units with incoming connections from unit k

A simple model: integrate-and-fire units

- Without interaction phases of all oscillators grow as $\varphi_k = \omega_k t$
- When phase of the oscillator k attains $\varphi_k = 2\pi$, it **issues a spike**
- When unit j **receives** a spike from unit k , its phase is instantaneously reset according to its PRC $Z_j(\varphi)$:



Assumptions

- Weak interaction: phase description is justified
- PRC of a unit is the same for all incoming connections
PRCs of different units can differ!
- Coupling is bidirectional but generally asymmetric,
 $\epsilon_{km} \neq \epsilon_{mk}$
- Relaxation after pulse stimulation is fast

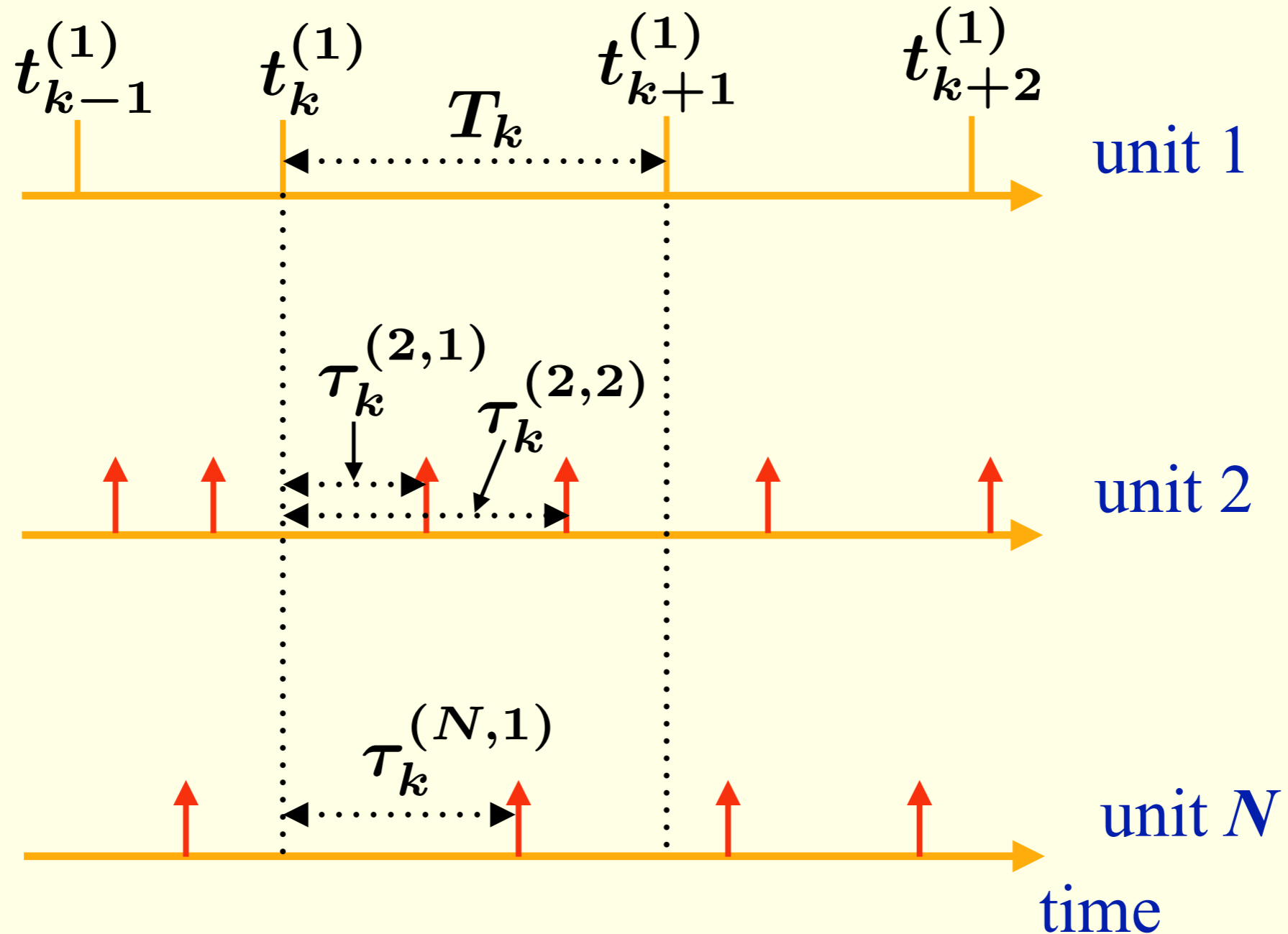
Our approach: iterative solution

- We choose one oscillator (let it be the first one) and consider its all incoming connections ϵ_{1m}
- For this oscillator, we recover:
 - its frequency
 - its PRC
 - strength of all incoming connections
- We achieve this in several iterative steps
- Then we repeat the procedure for all other units

Our approach: Notations

- Since we choose the first oscillator, we simplify notations by omitting one index
- For this oscillator, we recover:
 - its frequency ω
 - its PRC $Z(\varphi)$
 - strength of all incoming connections $\varepsilon_m, m = 2, \dots, N$

Notations II



When the spike at $\tau_k^{(i,l)}$ arrives, the phase of the first unit is

$$\varphi(t_k^{(1)} + \tau_k^{(i,l)}) = \varphi_k^{(i,l)}$$

Phase equation

Phase increase within each inter-spike interval is 2π

$$\omega T_k + \sum_{i=2}^N \varepsilon_i \sum_{l=1}^{n_k(i)} Z(\varphi_k^{(i,l)}) = 2\pi \quad (1)$$

Phase equation

Phase increase within each inter-spike interval is 2π

Network size

Number of stimuli from unit i

inter-spike interval

natural frequency

$$\omega T_k + \sum_{i=2}^N \varepsilon_i \sum_{l=1}^{n_k(i)} Z(\varphi_k^{(i,l)}) = 2\pi \quad (1)$$

PRC

strength of incoming connections

Phase of the first unit when it receives the l -th spike from unit i , within the inter-spike interval number k

Our approach: main idea

$$\omega T_k + \sum_{i=2}^N \varepsilon_i \sum_{l=1}^{n_k(i)} Z(\varphi_k^{(i,l)}) = 2\pi \quad (1)$$

- Suppose we know phases and coupling coefficients; then we represent the PRC as a finite Fourier series; thus, we obtain M linear equations (1), where M is the number of inter-spike intervals; for long time series it can be solved, e.g., by LMS fit
- Suppose, vice versa, that we know phases and PRC; then we obtain a linear system to find coupling coefficients ε_j

Our approach: main idea

$$\omega T_k + \sum_{i=2}^N \varepsilon_i \sum_{l=1}^{n_k(i)} Z(\varphi_k^{(i,l)}) = 2\pi \quad (1)$$

- Thus:
- φ_k, ε_i are known \longrightarrow we find Z, ω
 - φ_k, Z is known \longrightarrow we find ε_i, ω

Our approach: iterative solution

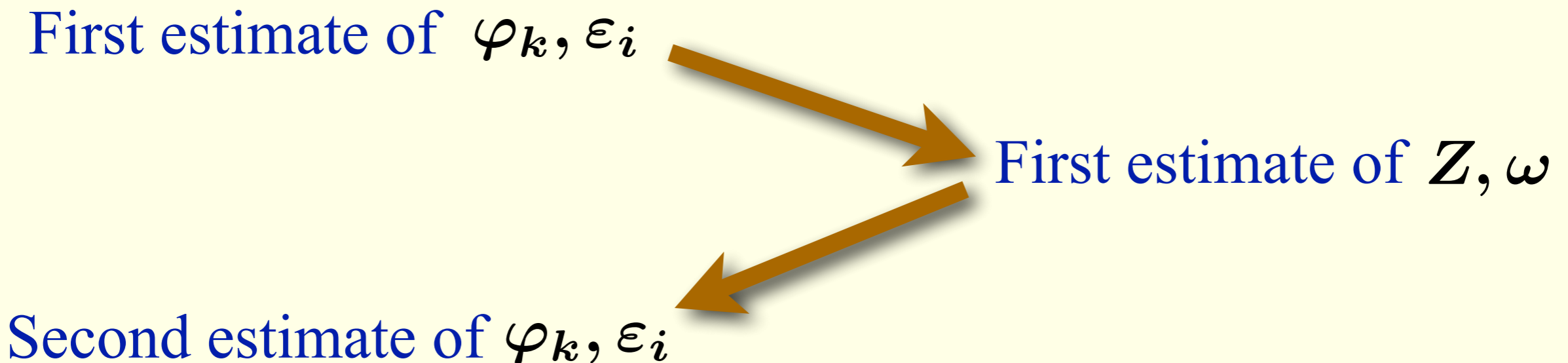
Thus: • φ_k, ε_i are known \longrightarrow we find Z, ω

• φ_k, Z is known \longrightarrow we find ε_i, ω

First estimate of φ_k, ε_i \longrightarrow First estimate of Z, ω

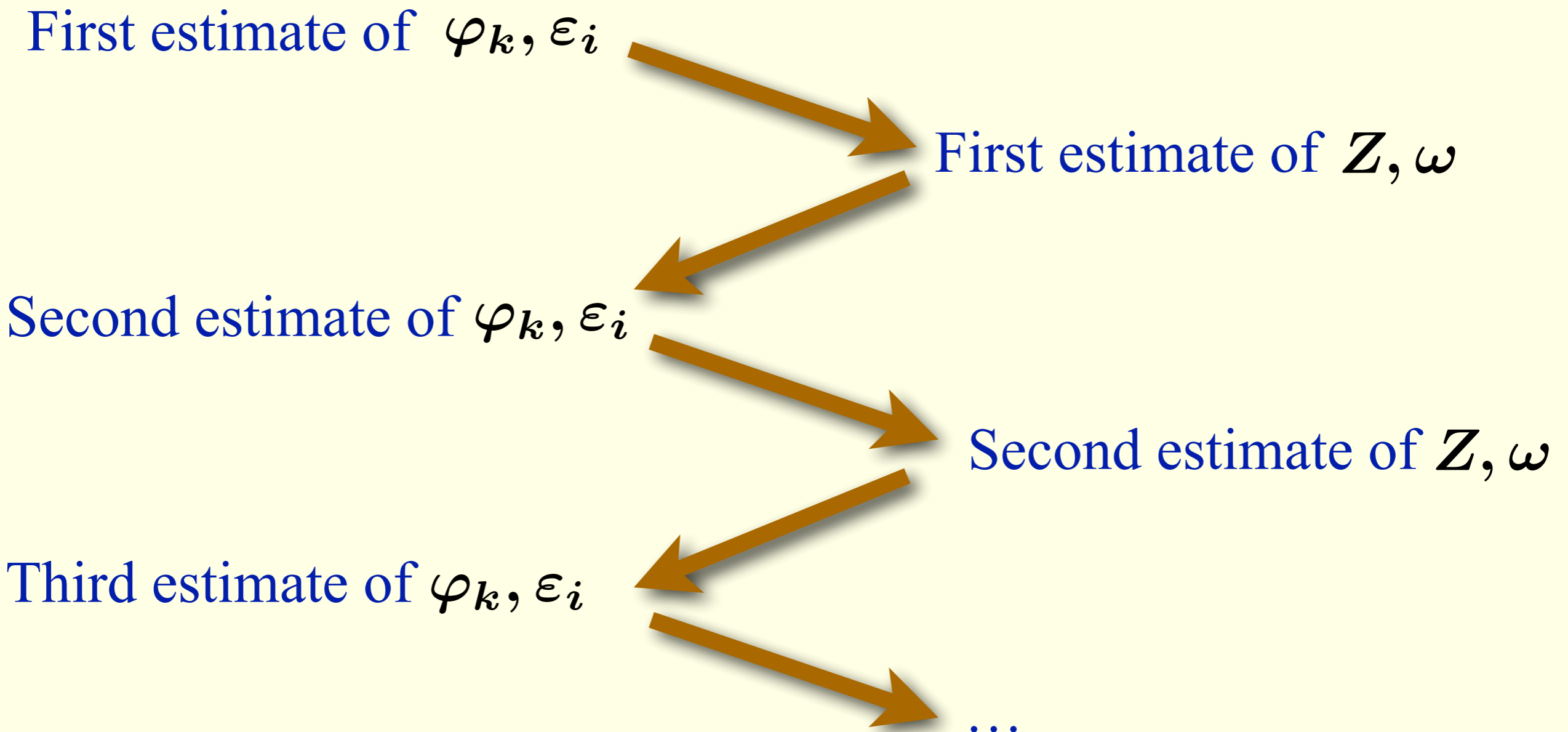
Our approach: iterative solution

- Thus:
- φ_k, ε_i are known \longrightarrow we find Z
 - φ_k, Z is known \longrightarrow we find ε_i



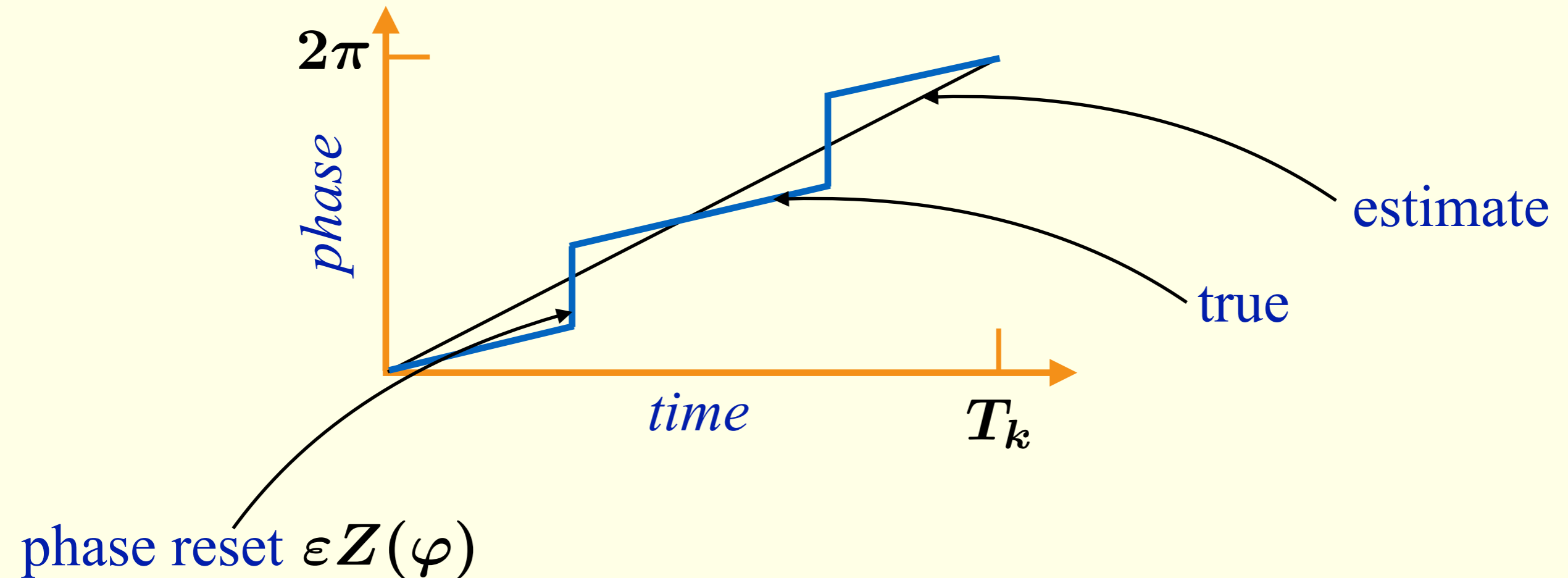
Our approach: iterative solution

- Thus:
- φ_k, ε_i are known \longrightarrow we find Z
 - φ_k, Z is known \longrightarrow we find ε_i



First estimate: phases

Initial estimate: proportionally to time $\varphi_k^{(i,l)} = 2\pi\tau_k^{(i,l)} / T_k$

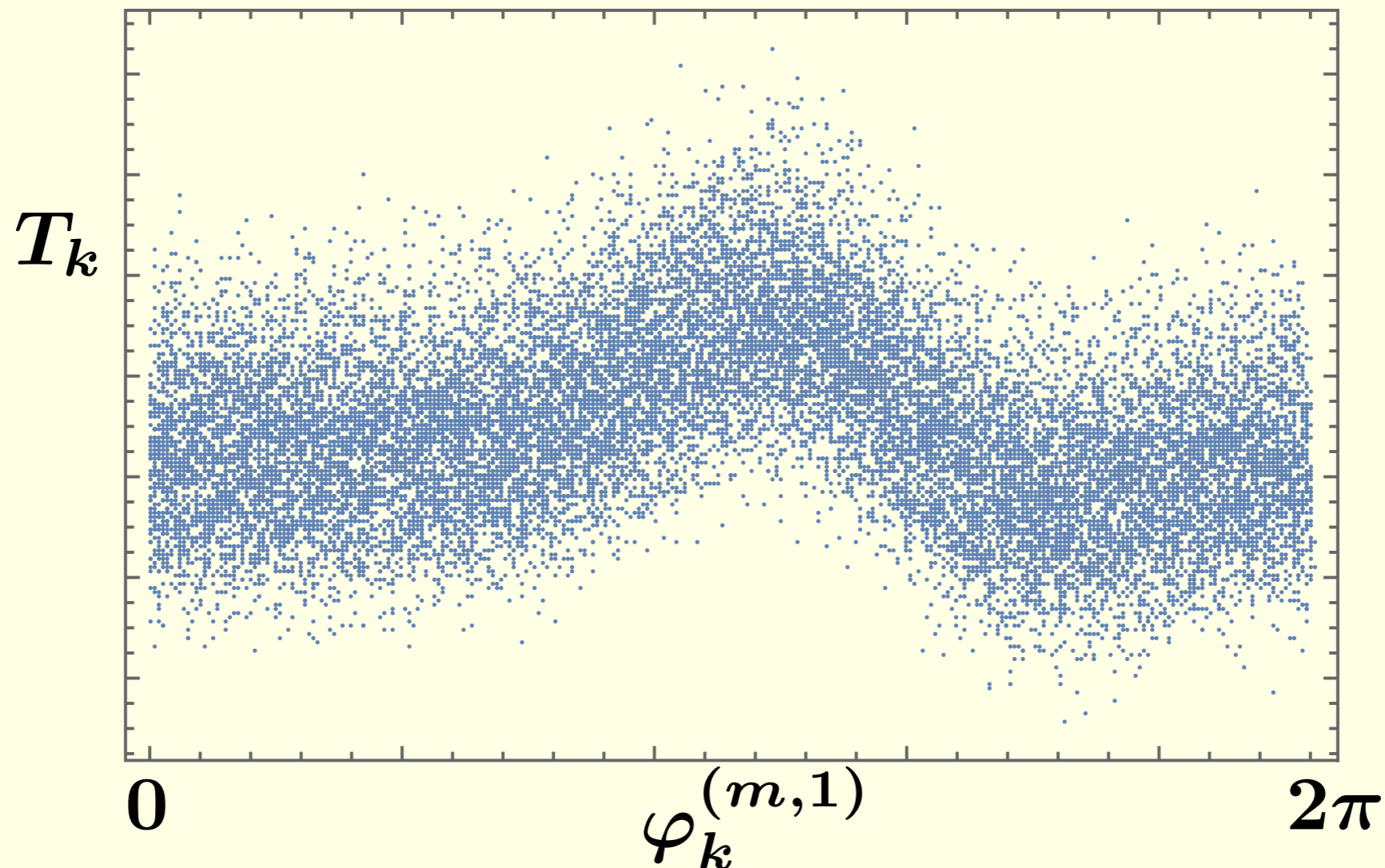


Error of the initial estimate is of the order of $\varepsilon Z(\varphi)$

First estimate: coupling coefficients

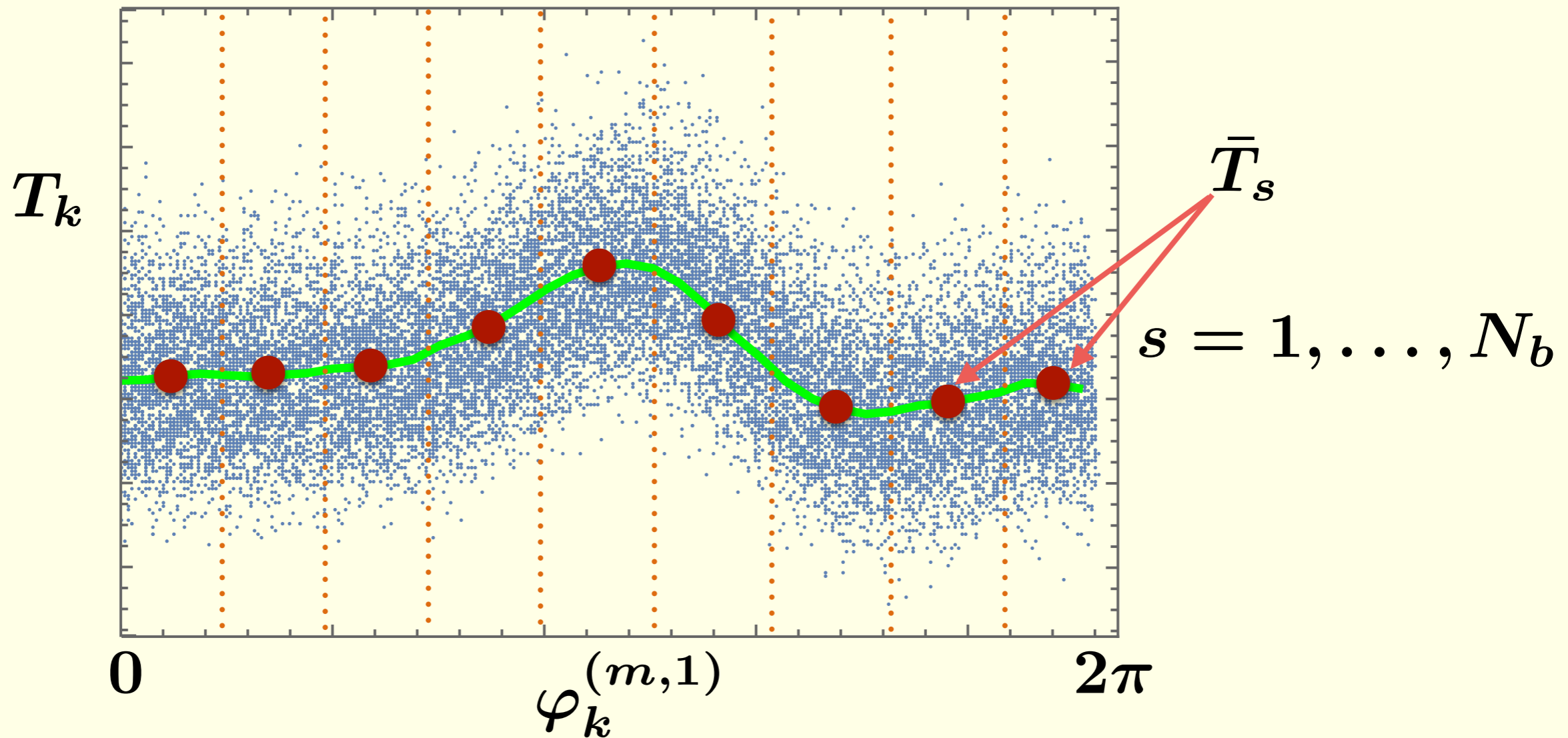
We want to estimate strength of the link from unit m to unit l

We plot the interval length T_k of the first unit vs the phase when the first stimulus from unit m arrives within this time interval



First estimate: coupling coefficients

Binning and averaging over N_b bins

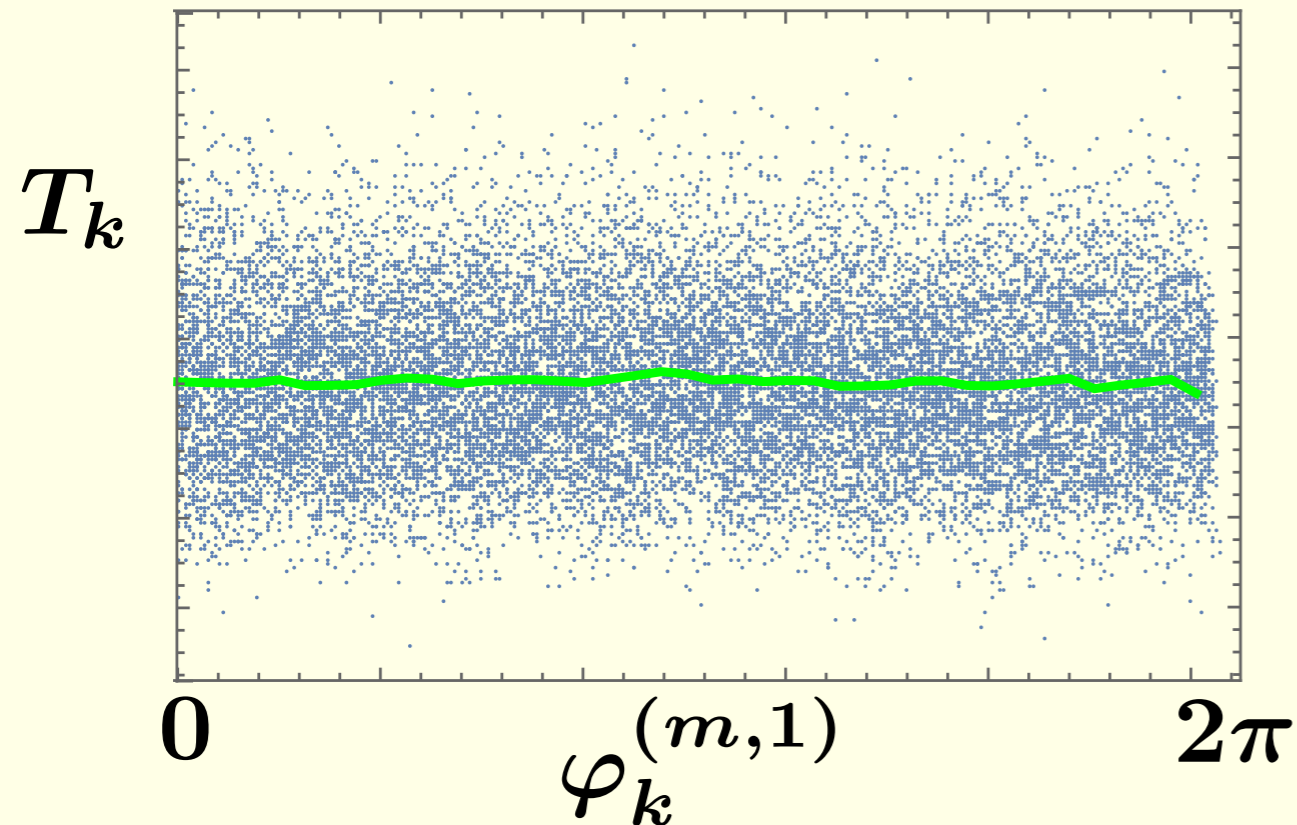


First estimate: $\varepsilon_m = \langle (\bar{T}_s - \langle \bar{T}_s \rangle)^2 \rangle^{1/2}$

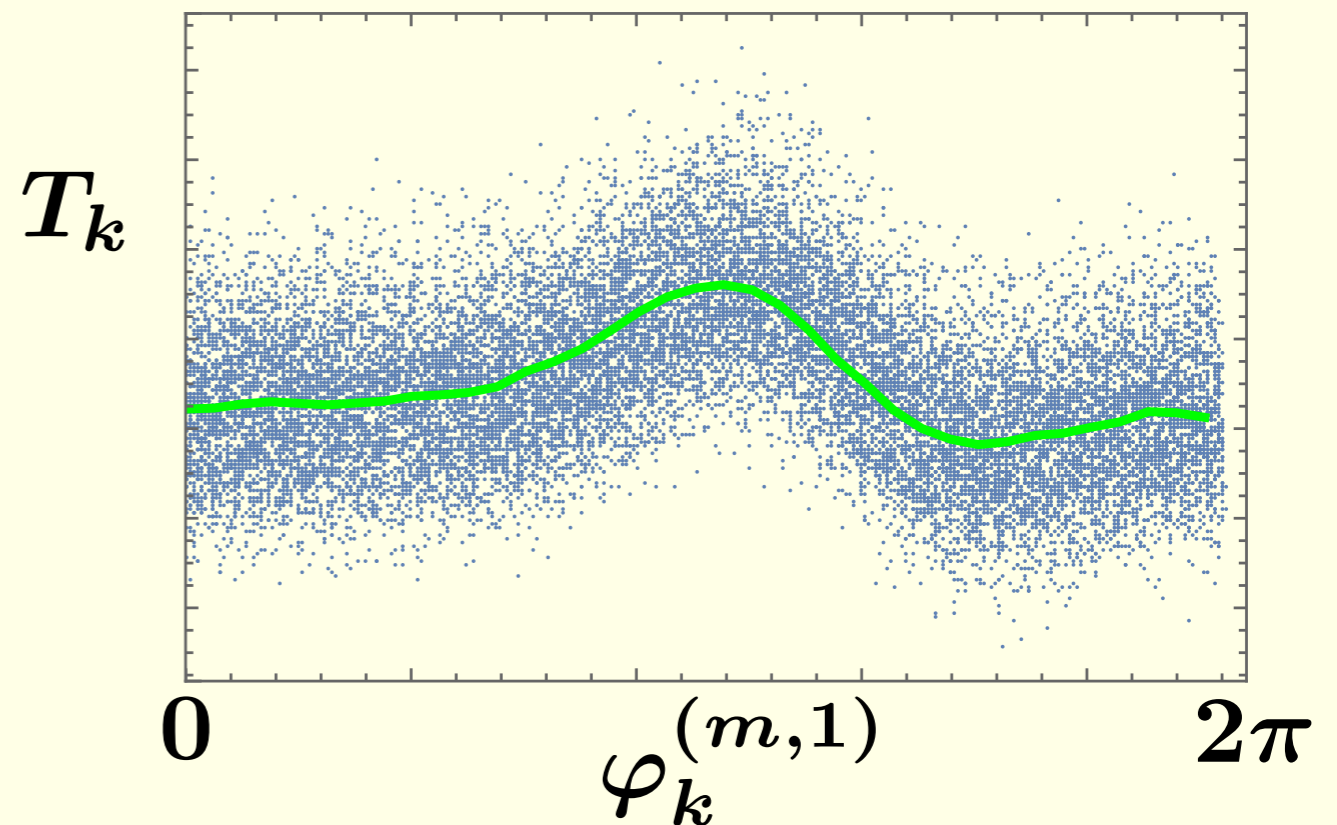
averaging over s

First estimate: coupling coefficients

Very weak coupling:
no dependence



Stronger coupling:
prominent dependence



First estimate: $\varepsilon_m = \langle (\bar{T}_s - \langle \bar{T}_s \rangle)^2 \rangle^{1/2}$

Next estimates: phases

An example: within T_k there are three incoming stimuli at

$$\tau_k^{(i,1)} < \tau_k^{(m,1)} < \tau_k^{(n,1)}$$

1st stimulus: $\varphi_k^{(i,1)} = \omega \tau_k^{(i,1)}$

2nd stimulus: $\varphi_k^{(m,1)} = \omega \tau_k^{(m,1)} + \varepsilon_i \mathbf{Z}(\varphi_k^{(i,1)})$

3rd stimulus: $\varphi_k^{(n,1)} = \omega \tau_k^{(n,1)} + \varepsilon_i \mathbf{Z}(\varphi_k^{(i,1)}) + \varepsilon_m \mathbf{Z}(\varphi_k^{(m,1)})$

At the end of the interval:

$$\psi = \omega T_k + \varepsilon_i \mathbf{Z}(\varphi_k^{(i,1)}) + \varepsilon_m \mathbf{Z}(\varphi_k^{(m,1)}) + \varepsilon_n \mathbf{Z}(\varphi_k^{(n,1)})$$

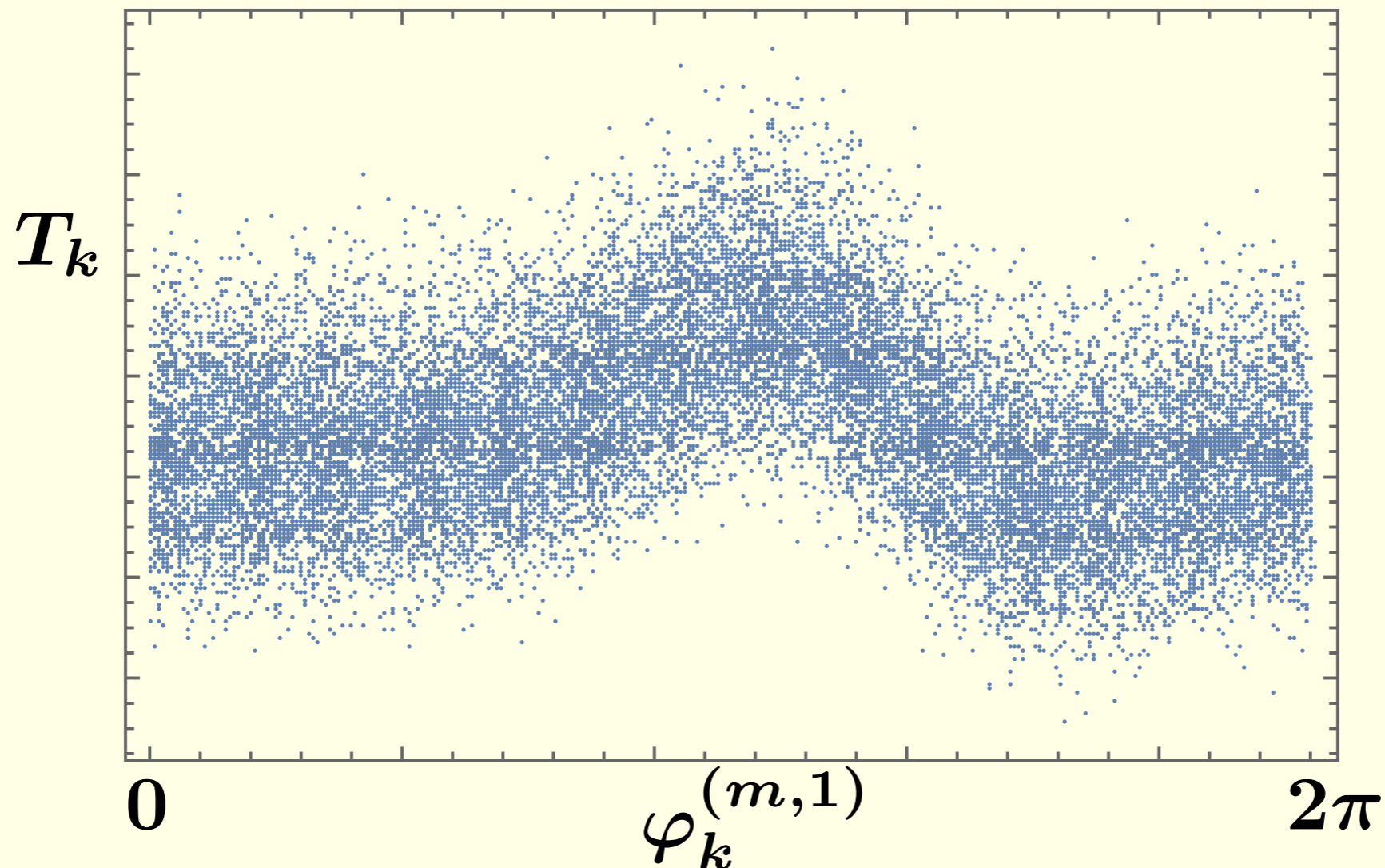
Our quantities are not precise  generally $\psi \neq 2\pi$

 we rescale all estimated phases by $2\pi / \psi$

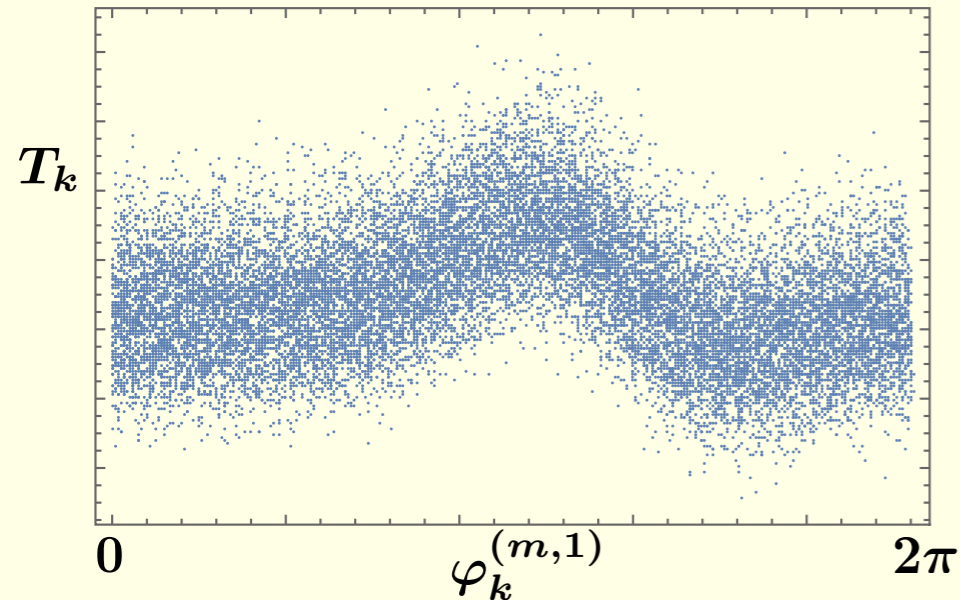
Coupling coefficients once again

We want to estimate strength of the link from unit m to unit l

We plot the interval length T_k of the first unit vs the phase when the first stimulus from unit m arrives within this time interval



Coupling coefficients once again



This approach works very good for a rather long time series

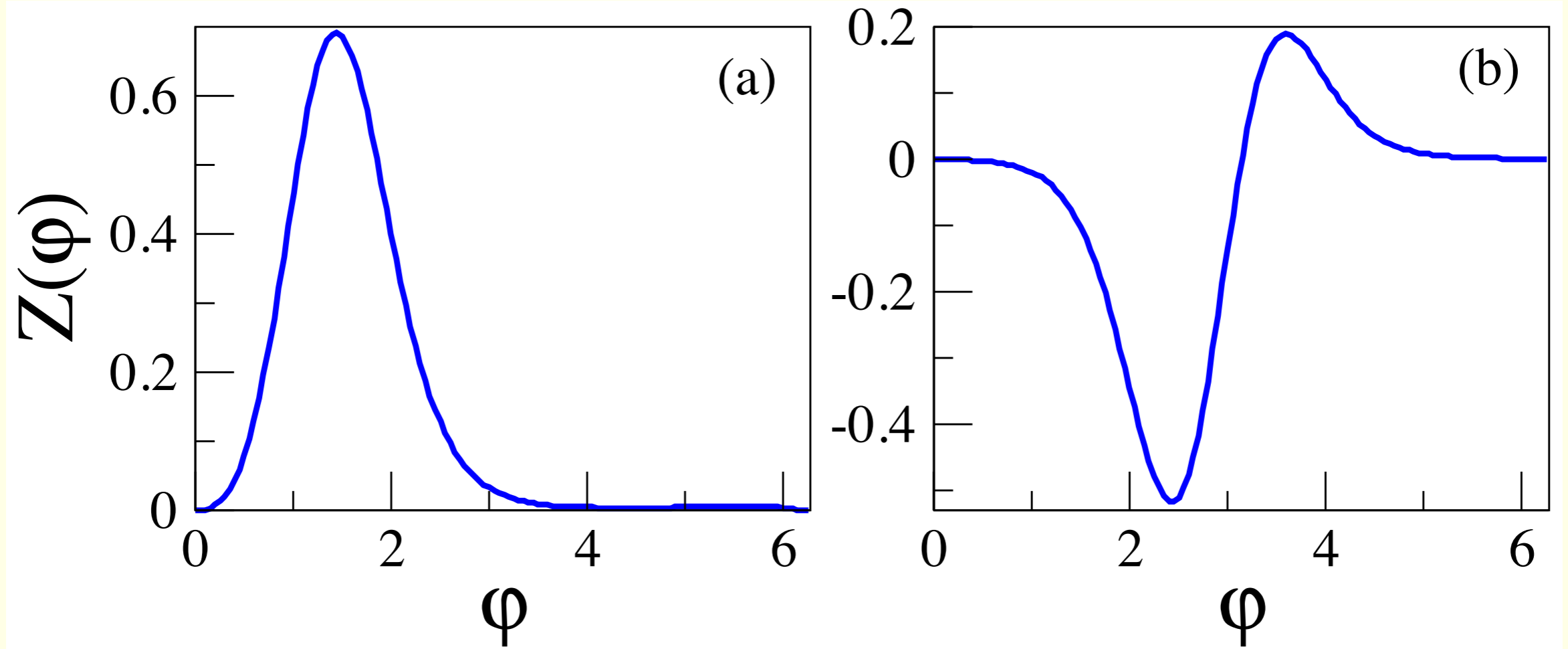
Numerical tests demonstrate that iterations converge to the correct value even for random assignment of initial values ε_i !

Numerical tests

Model phase response curves

Type I PRC

Type II PRC



Numerical tests: a remark on normalization

Recall the main equation:

$$\omega T_k + \sum_{i=2}^N \varepsilon_i \sum_{l=1}^{n_k(i)} Z(\varphi_k^{(i,l)}) = 2\pi$$

ε_i *and* Z enter it as a product

 ε_i *and* Z can be arbitrary rescaled

For comparison with the true values we choose scaling factor by minimizing

$$\sum_{i=2}^N \left[\varepsilon_i^{(t)} - c\varepsilon_i^{(r)} \right]$$

Numerical tests: a remark on normalization

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$$\sum_{i=2}^N \left[\varepsilon_i^{(t)} - c\varepsilon_i^{(r)} \right]$$

true ————— recovered

Numerical test I

Network size: $N = 20$

Natural frequencies: uniformly distributed between 1 and 2

$\omega_1 = 1$ (most difficult case)

Coupling coefficients: sampled from the positive part of a Gaussian distribution with zero mean and std 0.02

We exclude the networks where at least two units synchronize!

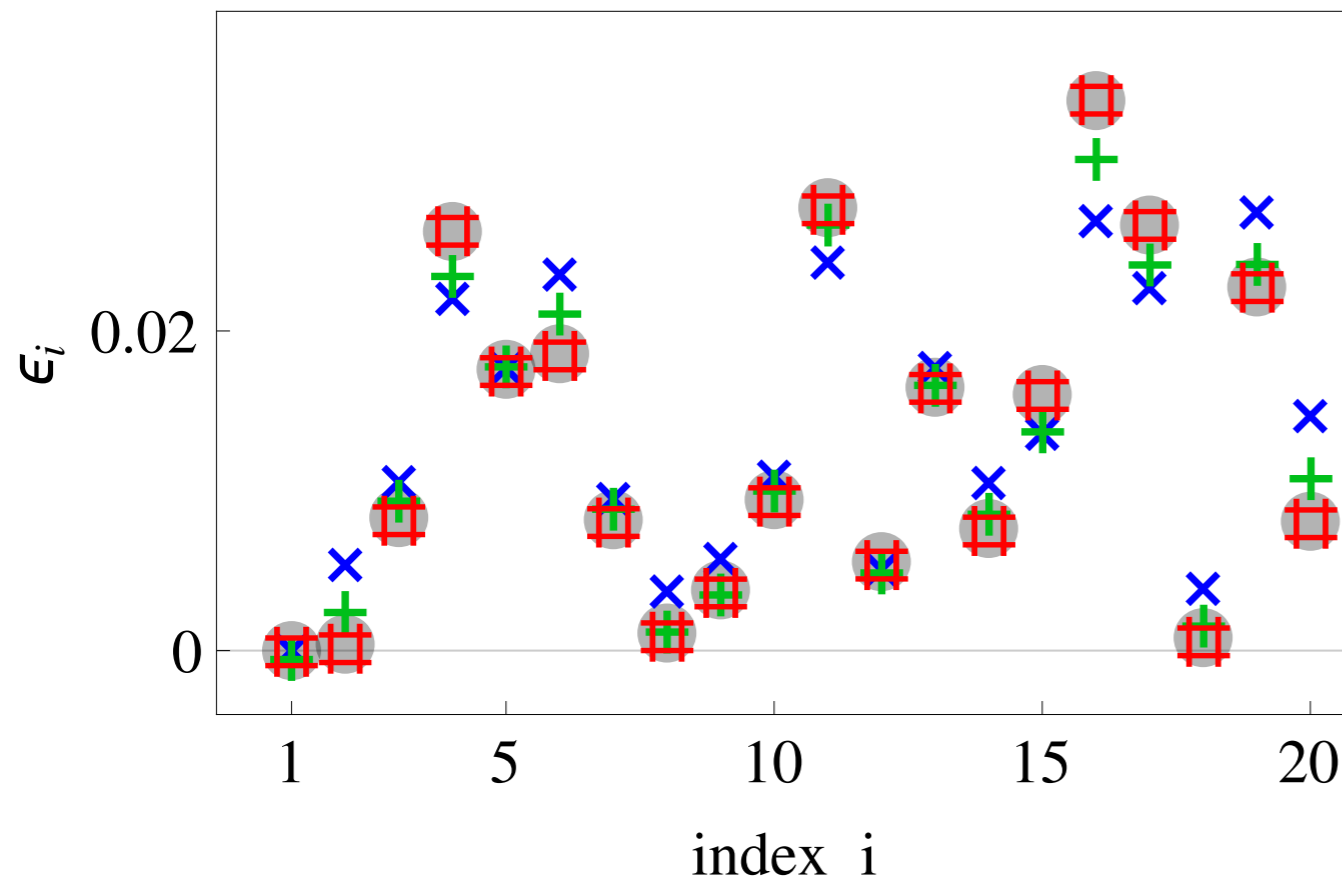
Reconstruction: 10 iterations, 10 Fourier harmonics

only 200 inter-spike intervals used

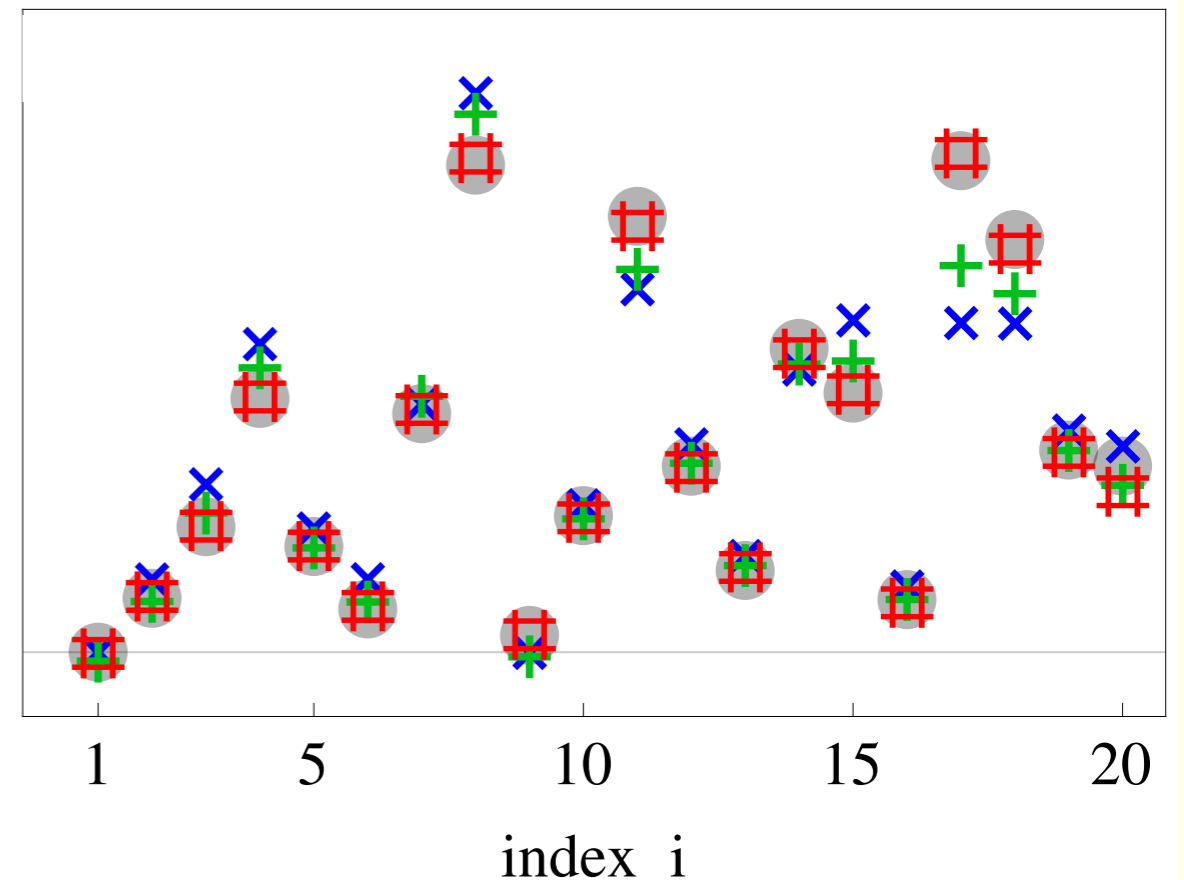
initial values $\varepsilon_i = 1, \forall i$

Iterative solution: results, coupling strength

Type I PRC



Type II PRC

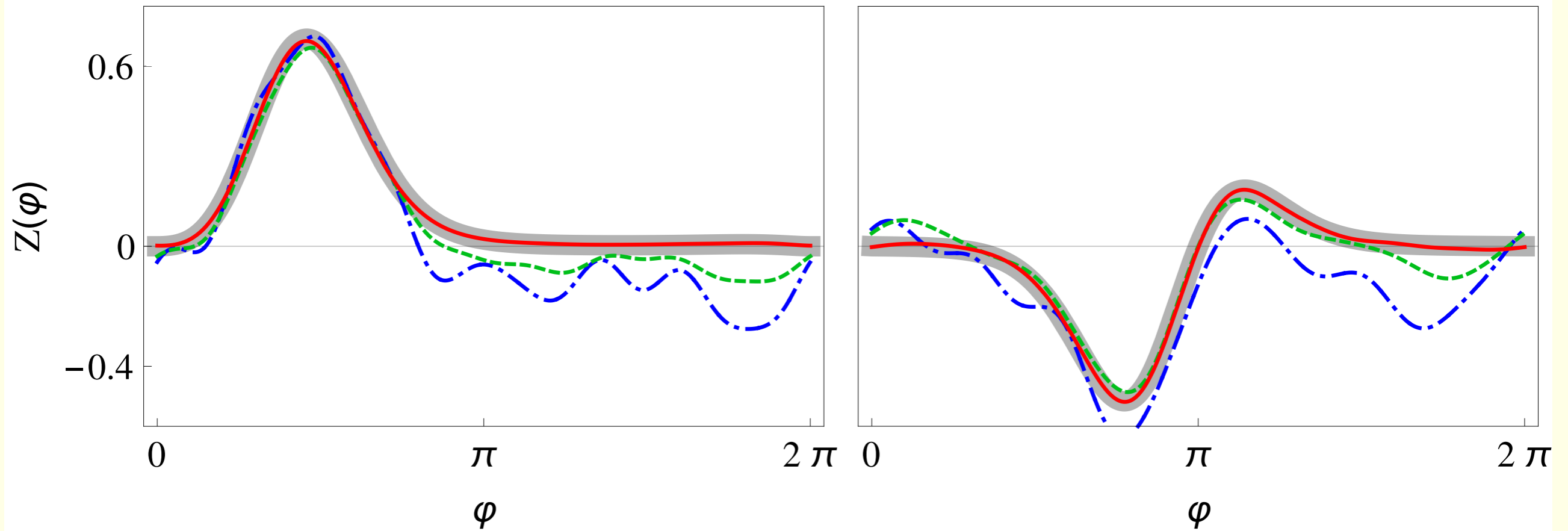






- true values
- + first iteration
- × second iteration
- ⊞ 10th iteration

Iterative solution: results, PRC

Type I PRC

Type II PRC

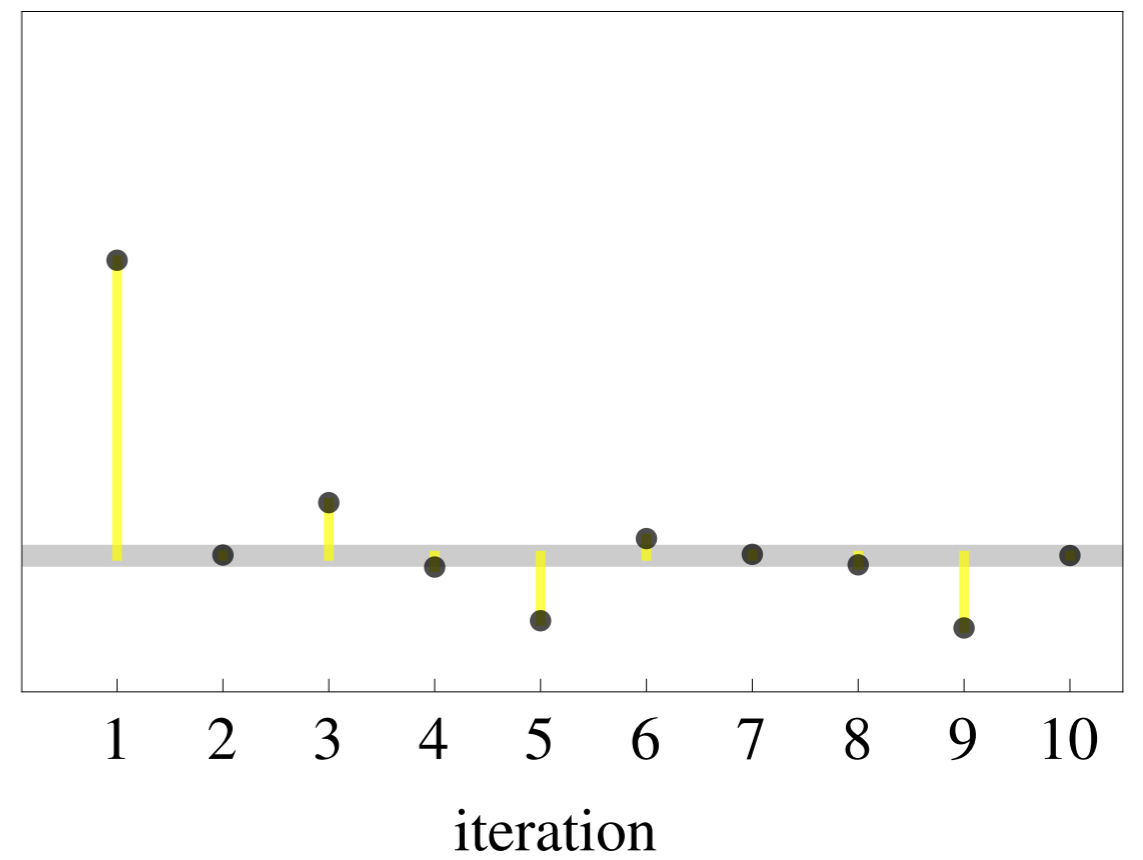
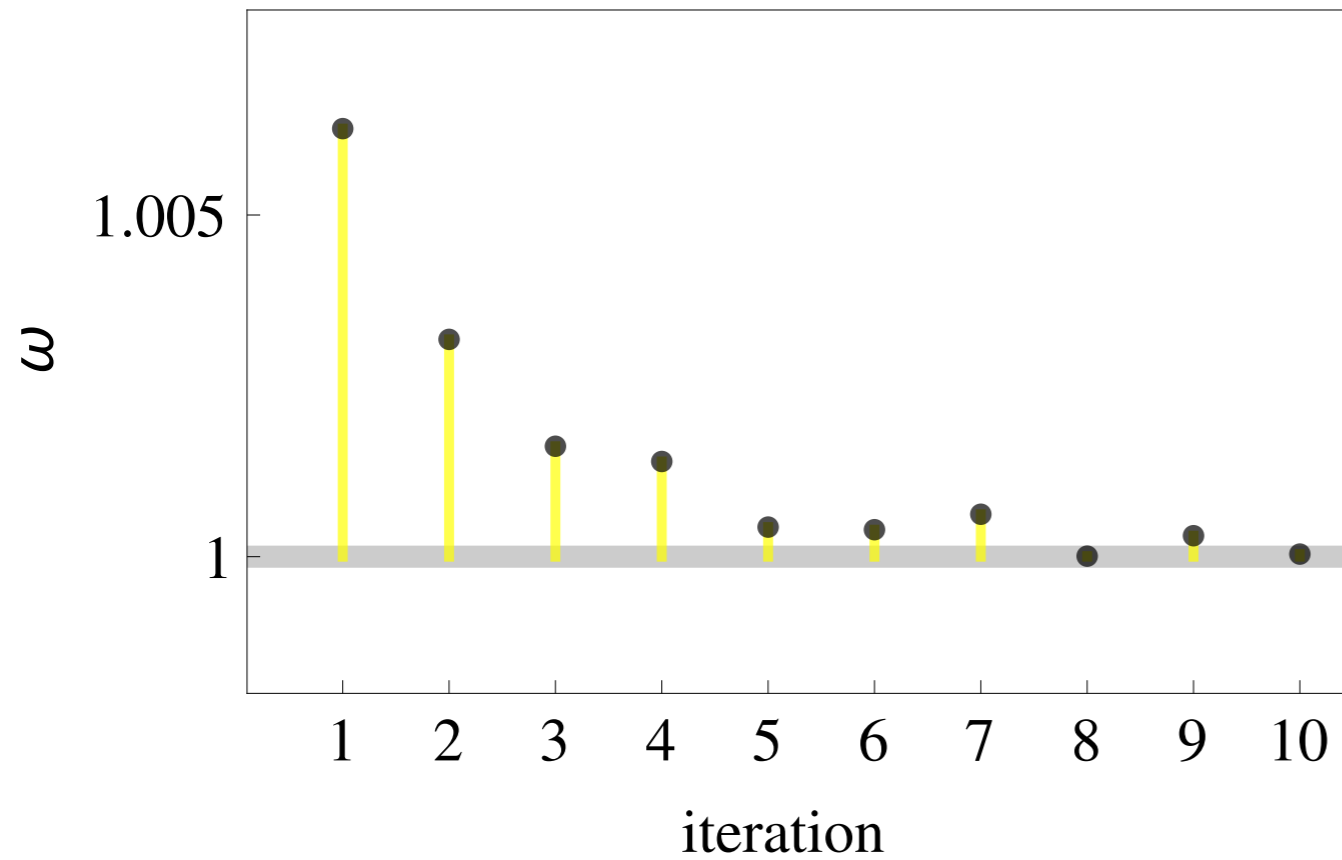


-  true PRC
-  first iteration
-  second iteration
-  10th iteration

Iterative solution: results, frequencies

Type I PRC

Type II PRC



— true value

Numerical test II: statistical analysis

Network size: $N = 20$

Natural frequencies: uniformly distributed between 1 and 2

$$\omega_1 = 1 \text{ (most difficult case)}$$

Coupling coefficients: sampled from the positive part of a Gaussian distribution with zero mean and std 0.02

We exclude the networks where at least two units synchronize!

Reconstruction: 10 iterations, 10 Fourier harmonics

only 200 inter-spike intervals used

initial values $\varepsilon_i = 1, \forall i$

We generate and reconstruct 10^5 networks

Numerical test II: statistical analysis

Quality of the reconstruction: we define the corresponding errors

$$\Delta_{\text{PRC}}^2 = \frac{\int_0^{2\pi} [Z^{(t)}(\varphi) - Z^{(r)}(\varphi)]^2 d\varphi}{\int_0^{2\pi} [Z^{(t)}(\varphi)]^2 d\varphi},$$

$$\Delta_{\varepsilon}^2 = \frac{\sum_{i=2}^N [\varepsilon_i^{(t)} - \varepsilon_i^{(r)}]^2}{\sum_{i=2}^N [\varepsilon_i^{(t)}]^2},$$

$$\Delta_{\omega}^2 = [\omega^{(t)} - \omega^{(r)}]^2$$

true

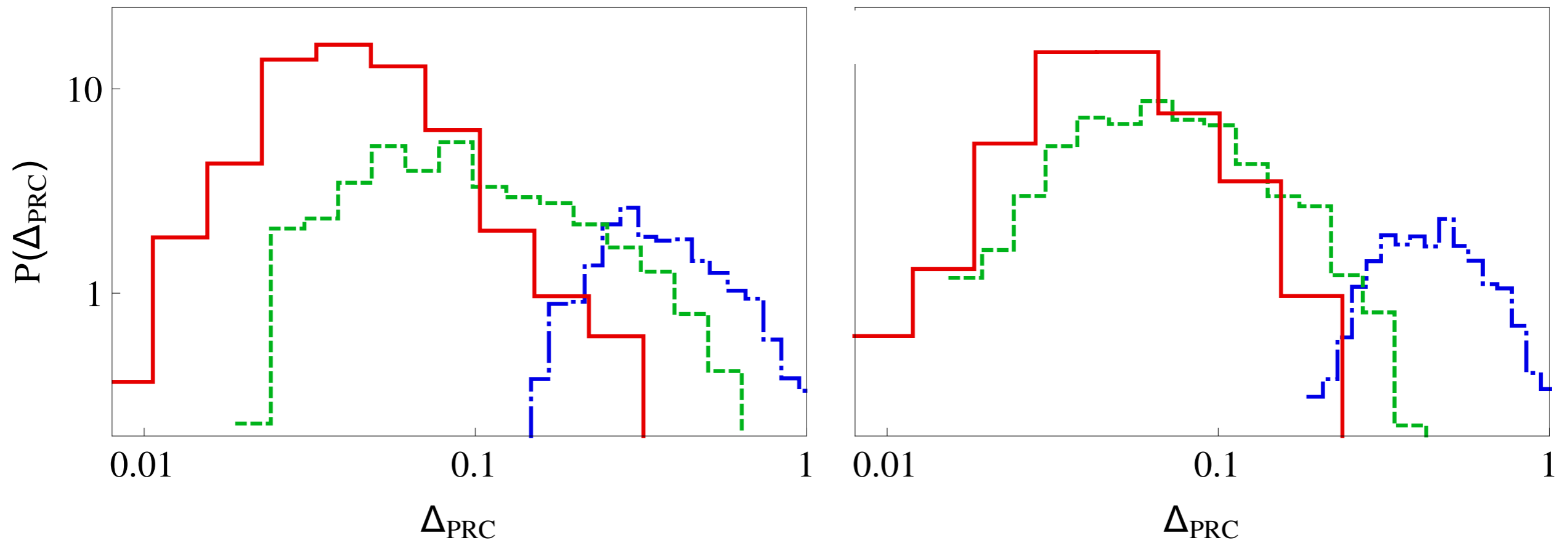


recovered

Numerical test II: results, histograms of errors

Type I PRC

Type II PRC

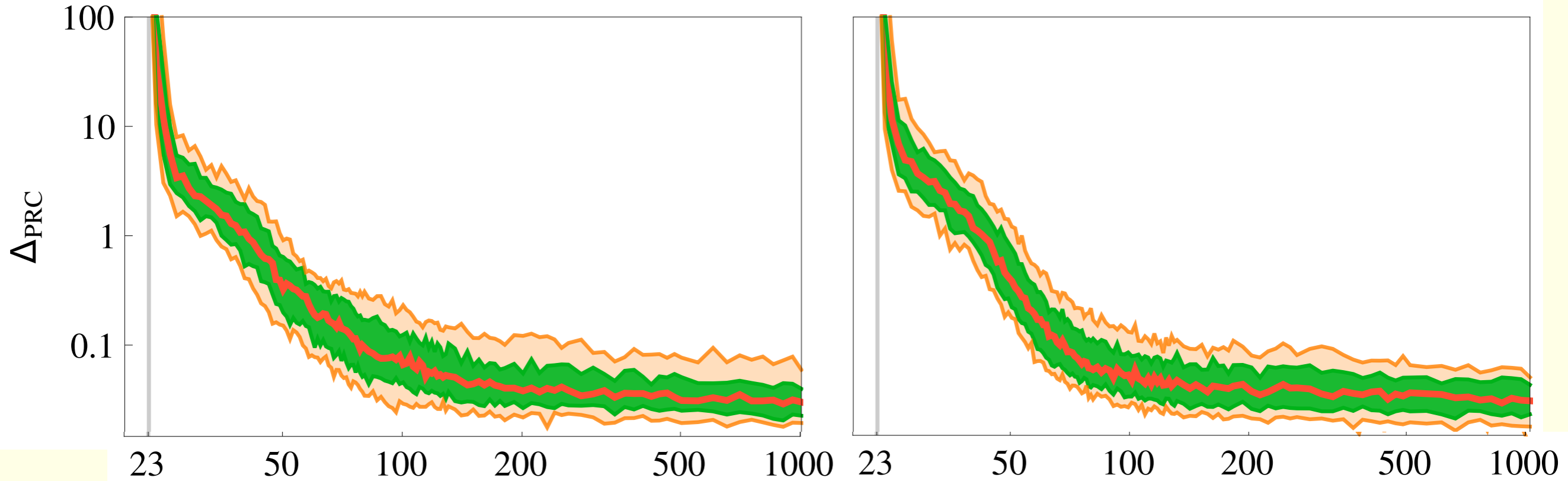


- · — · — first iteration
- - - third iteration
- 10th iteration

Numerical test II: results, impact of data length

Type I PRC

Type II PRC



number of inter-spike intervals used

Further tests: impact of network size and noise

Network size from $N=10$ to 500 , with number of spikes $\sim N$

Computational time: $\sim N^4$, in fact, small (minutes on a laptop)

Errors increase linearly with noise intensity

One step towards realistic modelling: Morris-Lecar neurons

$$\dot{V}_i = I_i - g_l(V_i - V_l) - g_K w_i(V_i - V_k) - g_{Ca} m_\infty(V_i)(V_{Ca} - V_i) + I_i^{(\text{syn})},$$

$$\dot{w}_i = \lambda(V_i)(w_\infty(V_i) - w_i),$$

$$m_\infty(V) = [1 + \tanh(V - V_1/V_2)]/2,$$

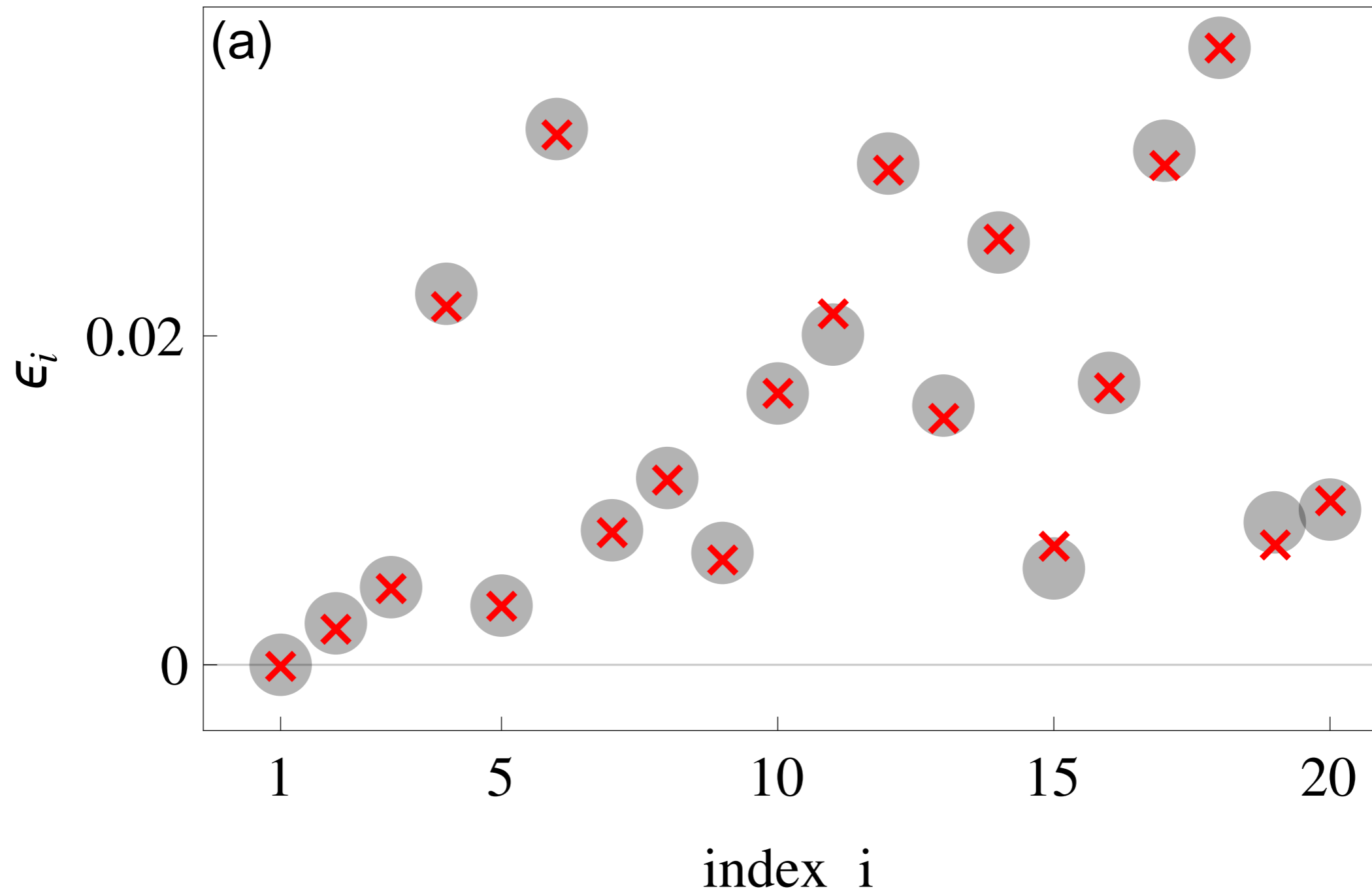
$$w_\infty(V) = [1 + \tanh(V - V_3/V_4)]/2,$$

$$\lambda(V) = \cosh[(V - V_3)/(2V_4)]/3,$$

with synaptic coupling

$$I_i^{(\text{syn})} = [V_{\text{rev}} - V_i] \sum_{k, k \neq i} \frac{\varepsilon_{ik}}{1 + \exp[-(V_k - V_{\text{th}})/\sigma]}$$

Morris-Lecar network: results, coupling strength

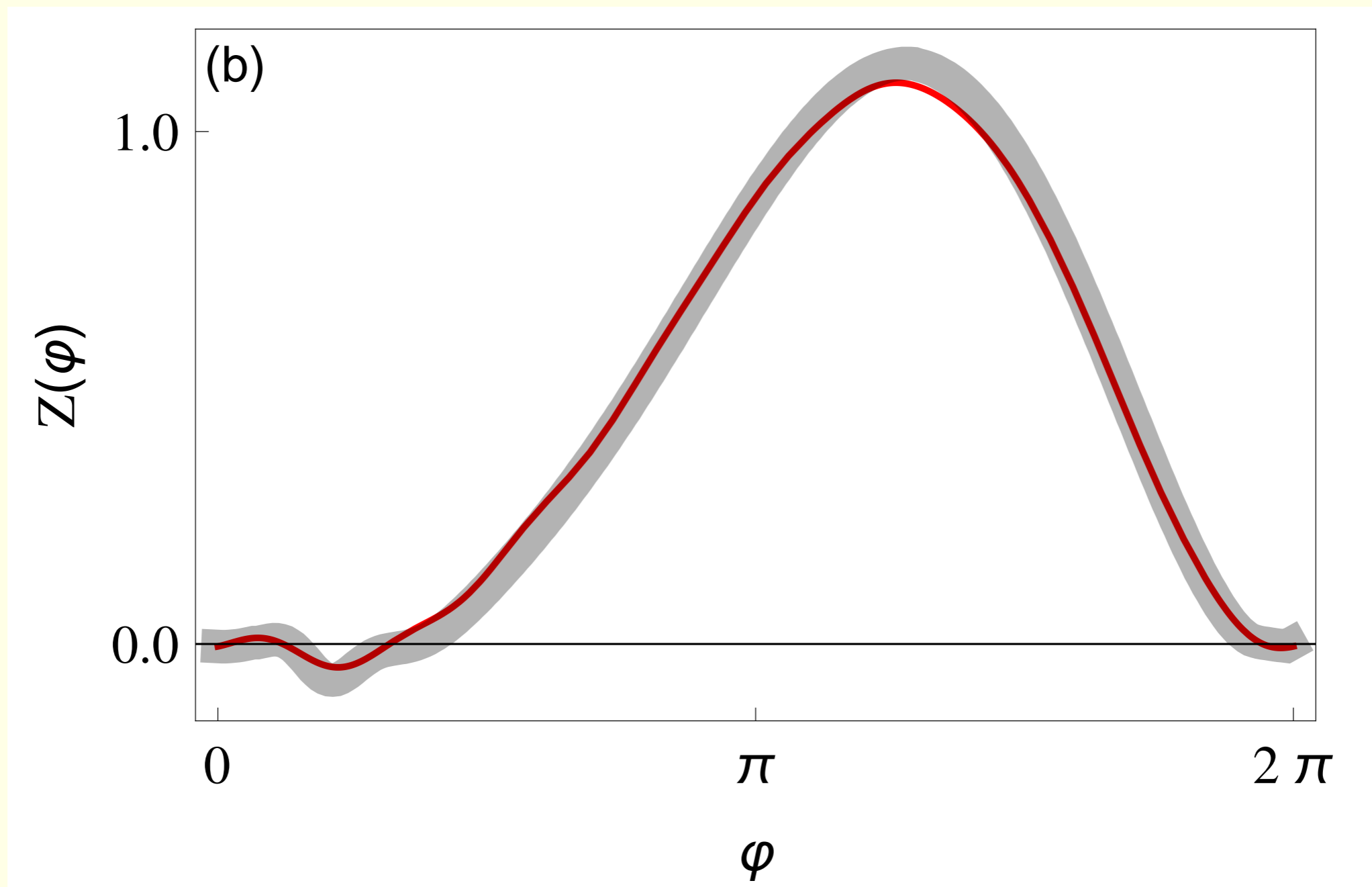


● true value

✗ after 10 iterations

only 200 inter-spike intervals are used!

Morris-Lecar network: results, PRC



— true PRC
— 10th iteration

Conclusions

- Robust reconstruction of the network structure already for several hundreds of spikes
- Works if the network does not synchronize
- If the coupling is not weak enough: the network reconstruction remains correct, the PRC is amplitude-dependent
- Error of the phase estimation increases with the number of spikes \implies the reconstruction may fail for $\omega_i/\omega \gg 1$
- We need some variability in the drive: the reconstruction may fail for very sparse networks where periodic nodes can be found (however, noise helps here!)

Conclusions II

- Reference: Phys. Rev. E **96**, 012209 (2017)



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Thank you for your attention!