

Computational Approaches to Signal Processing for Sleep

An Introduction to Network Analysis & EEG
Interpretation

June 2021

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Outline

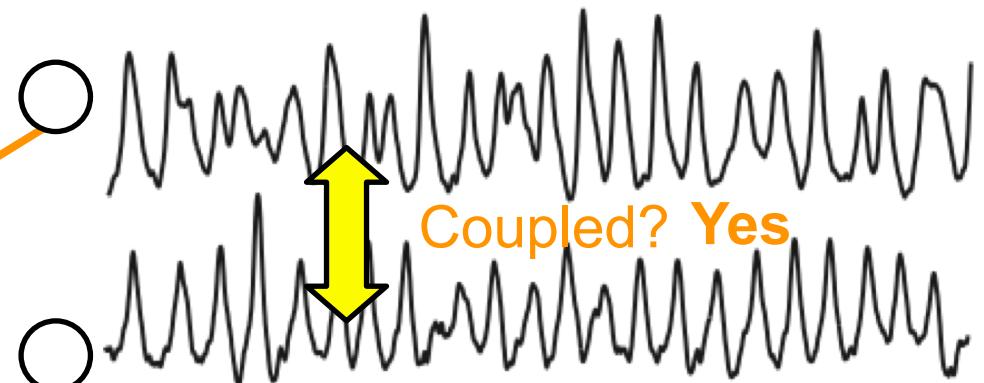
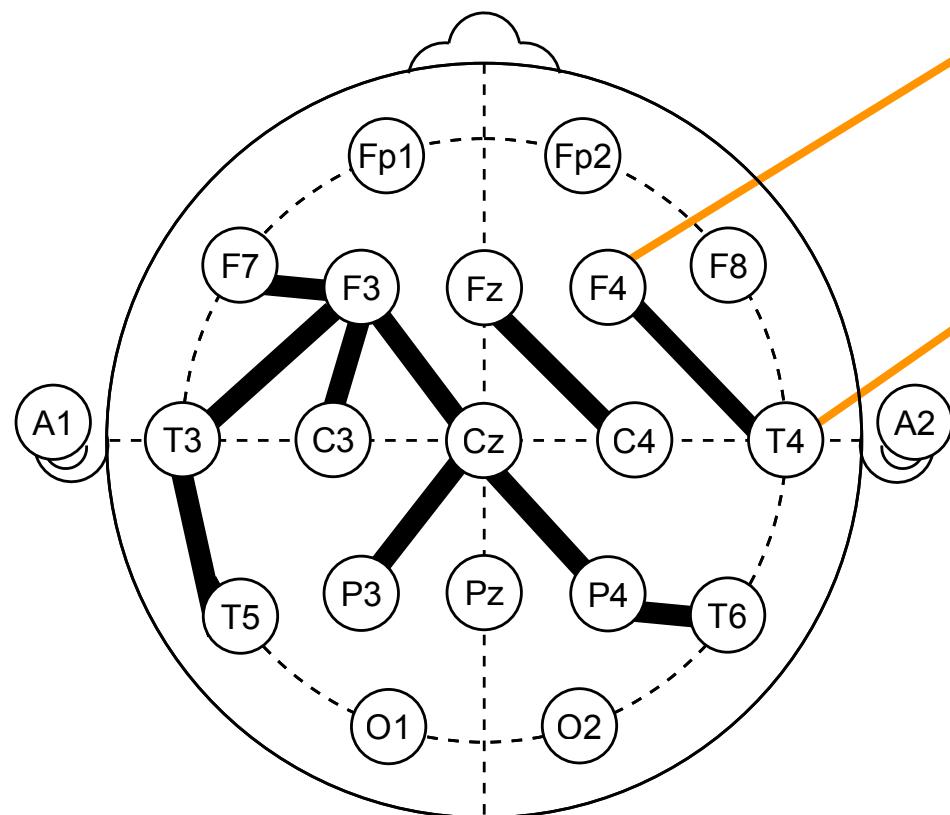
- Functional connectivity (epilepsy)
- Data analysis pipeline: data → network
- Example application: sleep spindles

Motivating question

Which signals are coupled, and when?

Functional Connectivity

Multiple electrodes



Long history

[Brazier, 1972 & 1973; Gotman, 1981 & 1983; ...]

Many coupling measures

[Pereira et al, 2005; Greenblatt et al, 2012]

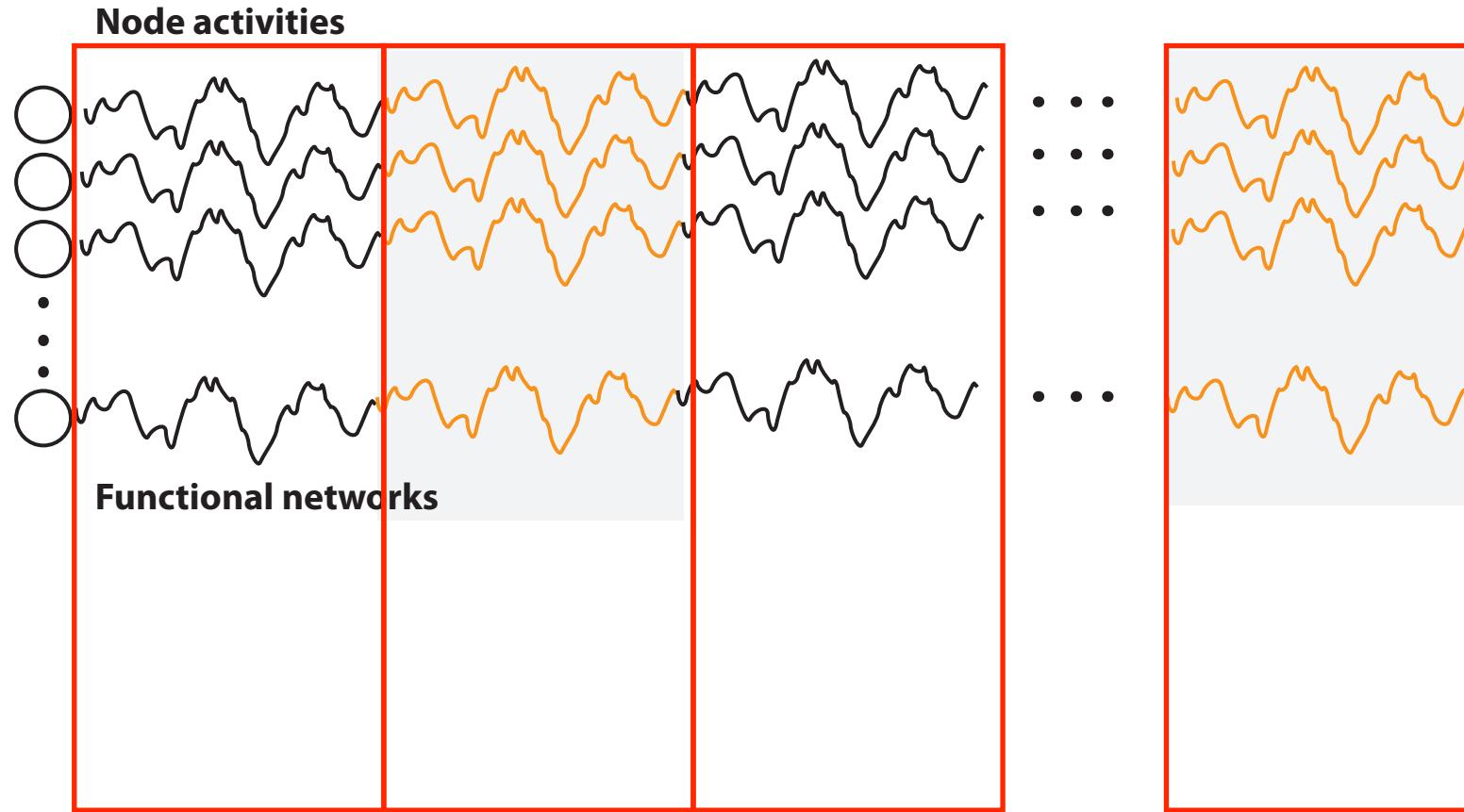
Repeat for all electrode pairs:

Functional network:



Functional Connectivity

Networks evolving in time



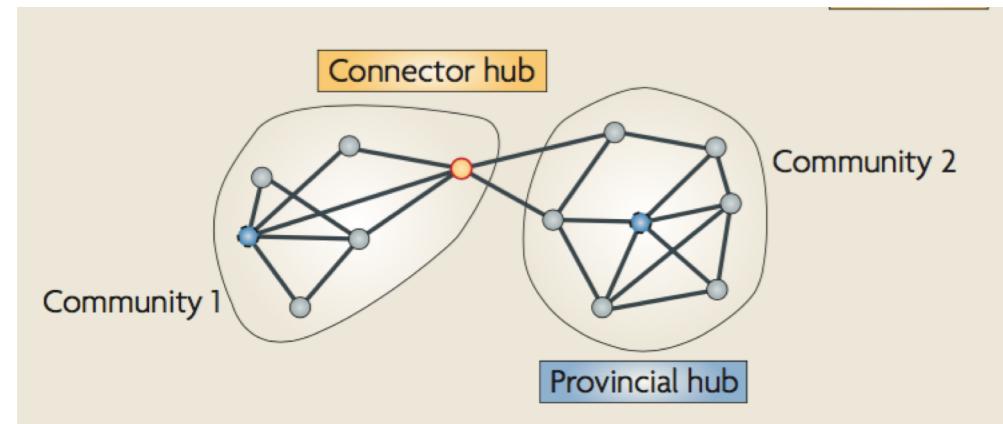
Q: How do functional networks evolve (during seizure)?

[Kramer and Cash, 2012]

One example ...

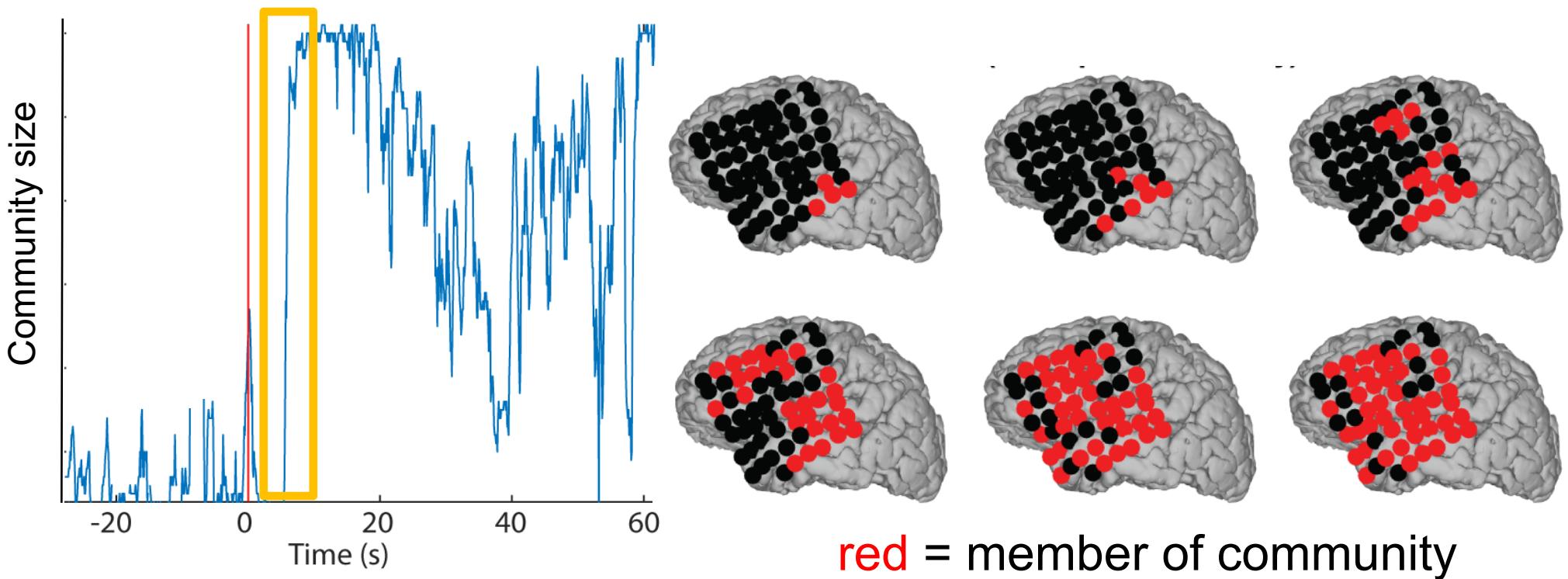
Example

... sudden emergence of a large community at seizure onset.



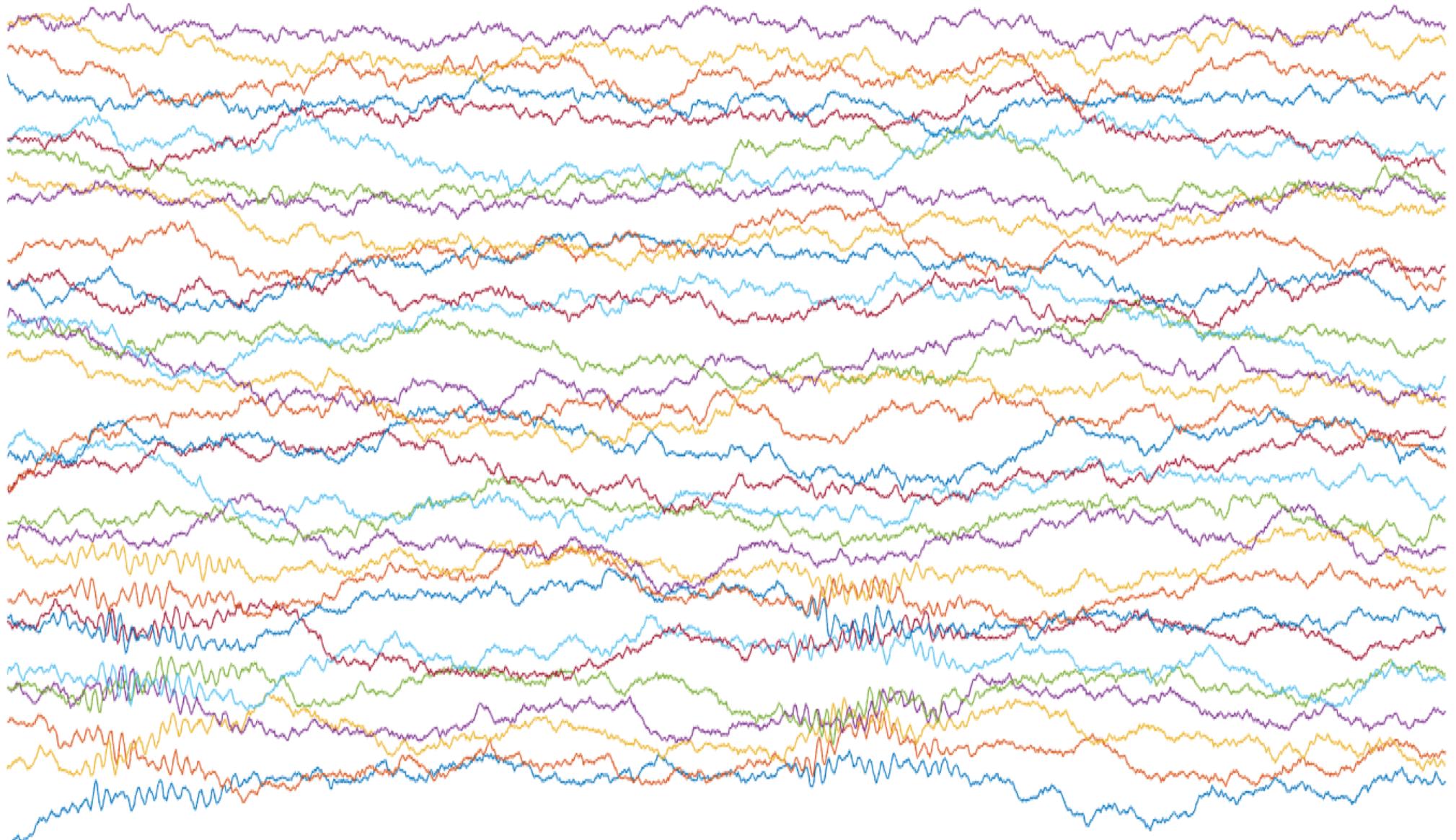
[Bassett and Sporns 2017]

Large community suddenly forms



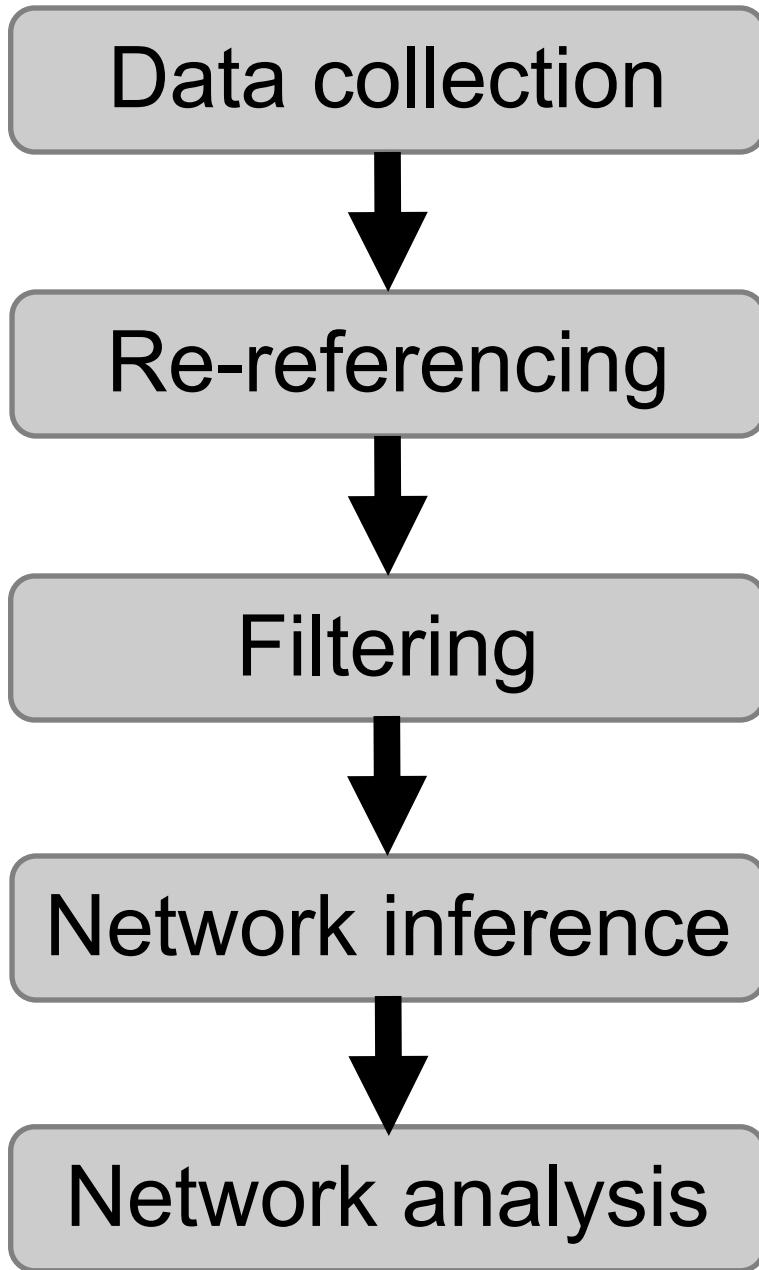
How seizure spreads on cortex? [Martinet, Kramer et al., Nat Comm, 2020]

Challenge



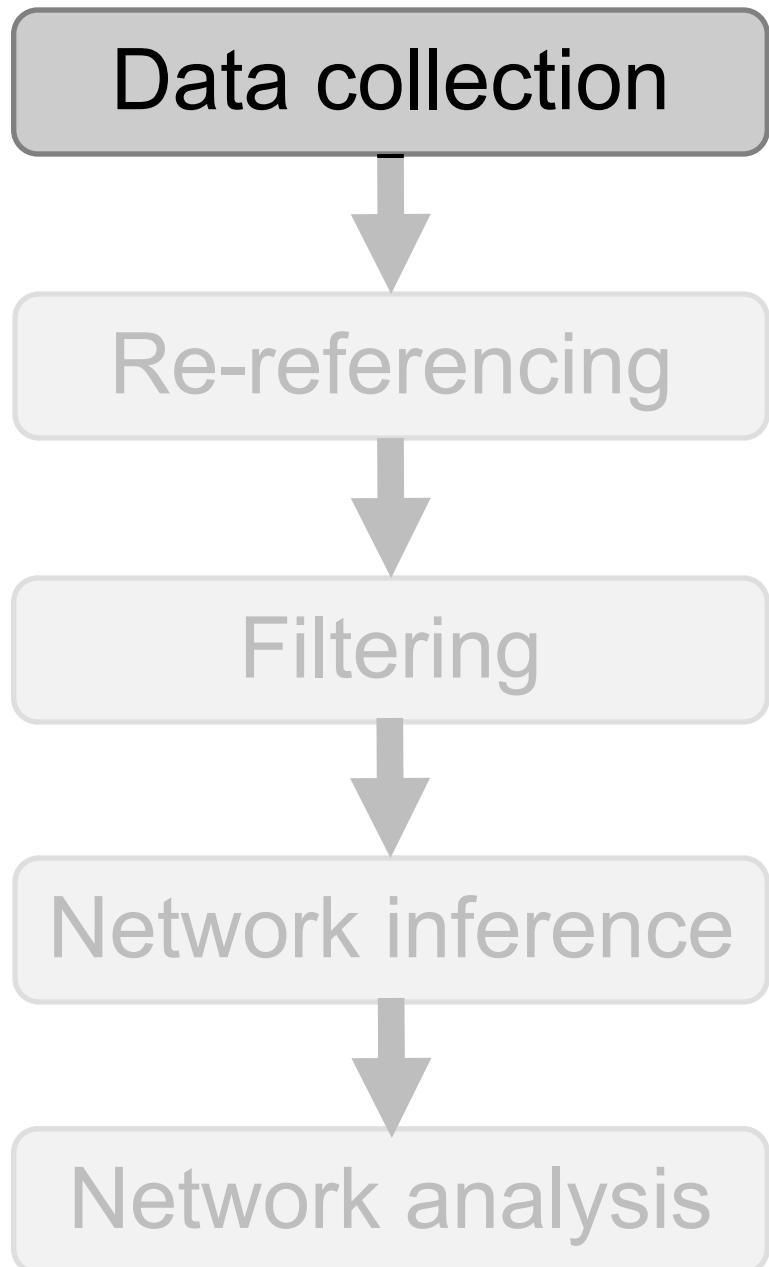
Which electrodes are coupled?

Pipeline

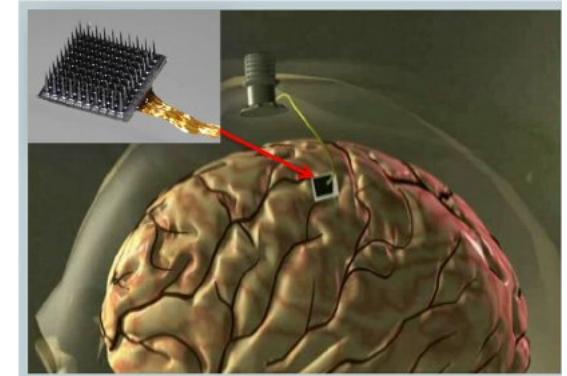


Each step, a new challenge

Pipeline



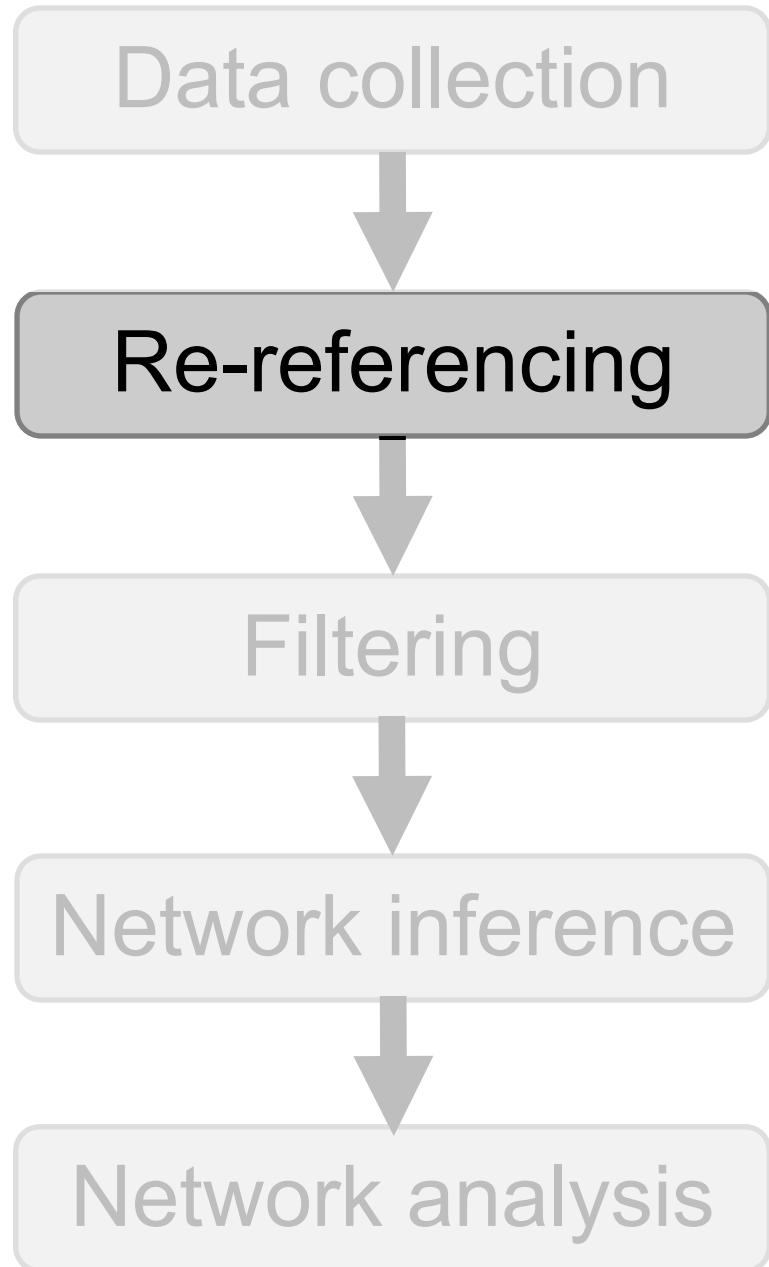
- Brain coverage vs spatial sampling.



[Nurmikko et al, 2010]

- EEG: high or low density ... nodes in the network
- Sampling rate ... rhythms observable

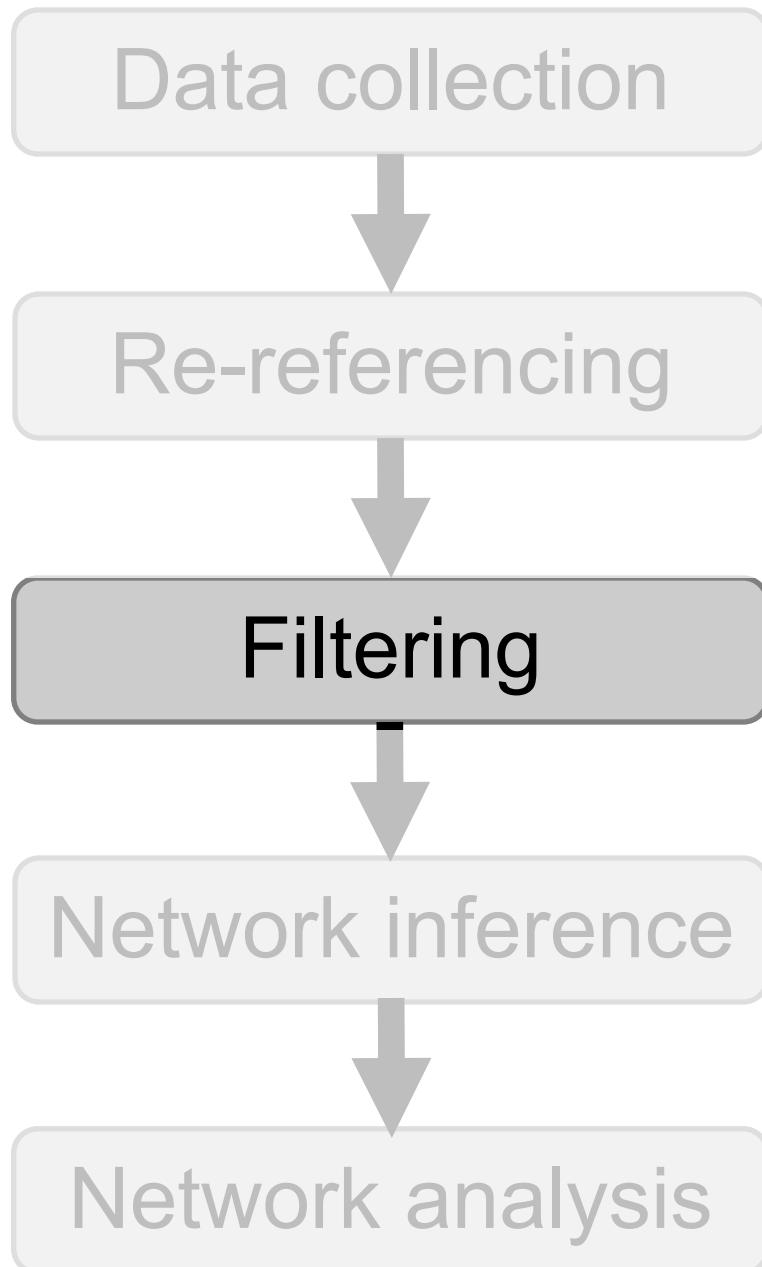
Pipeline



- Physical
- Bipolar
 - ... reduces number of nodes.
- Common average
 - ... introduces shared signal?
- Laplacian
- Reference electrode standardization technique (REST)

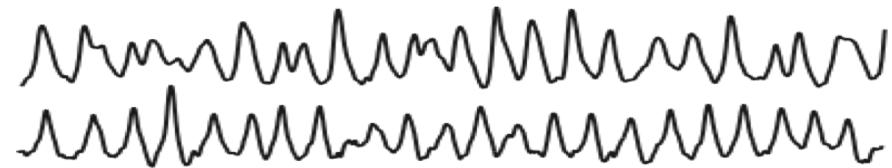
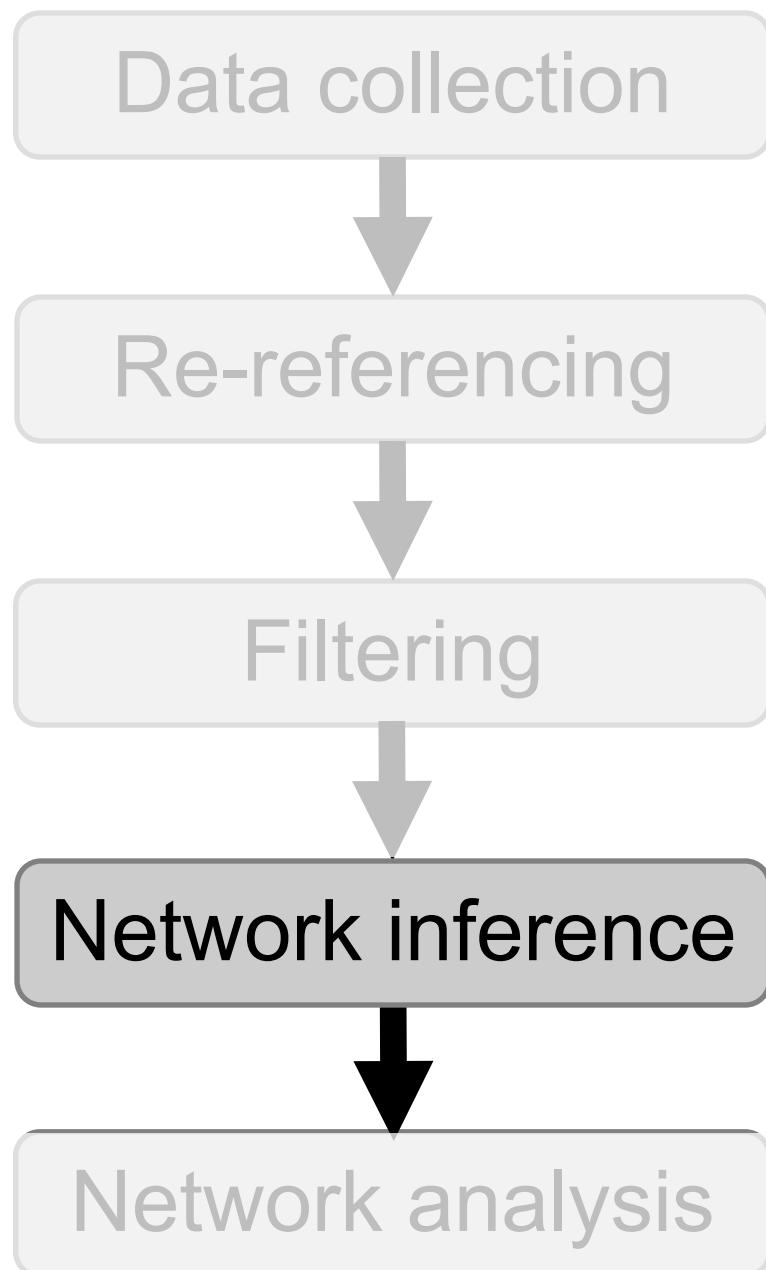
[Chella et al, J Neural Eng, 2016]
[Nunez & Srinivasan, 2005]

Pipeline



- Which frequency band?
 - ... to keep: delta, HFO
 - ... to remove: sweat artifact, 60 Hz
- Filter parameters
 - Type:
 - FIR, IIR, ...
 - High-pass, low-pass, ...

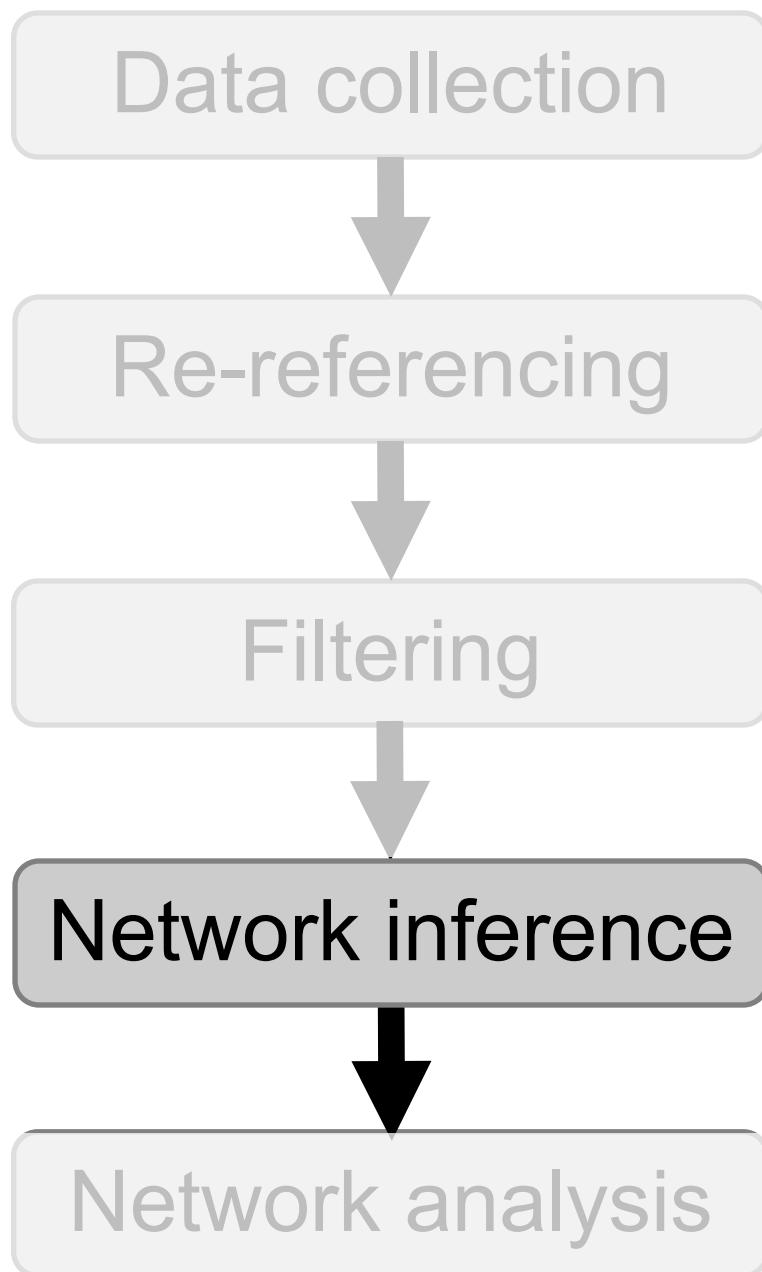
Pipeline



Coupling measure

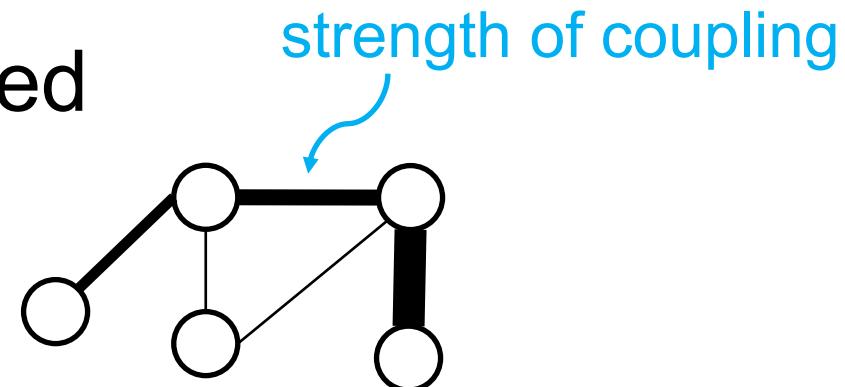
- **Linear (correlation)**
... simple, fast, well understood
- **Nonlinear (information)**
... powerful, more complex
- **Model based (Granger)**
... address confounds, slow
 - [Spencer et al 2018; Greenblatt et al 2012; Pereda et al 2005; Nunez et al, 1997]

Pipeline

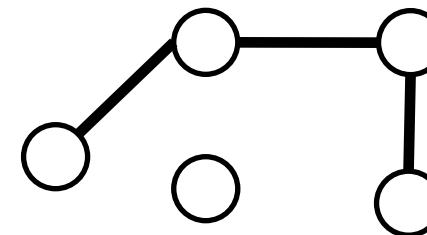


Apply the coupling measure,
then create the network:

Weighted



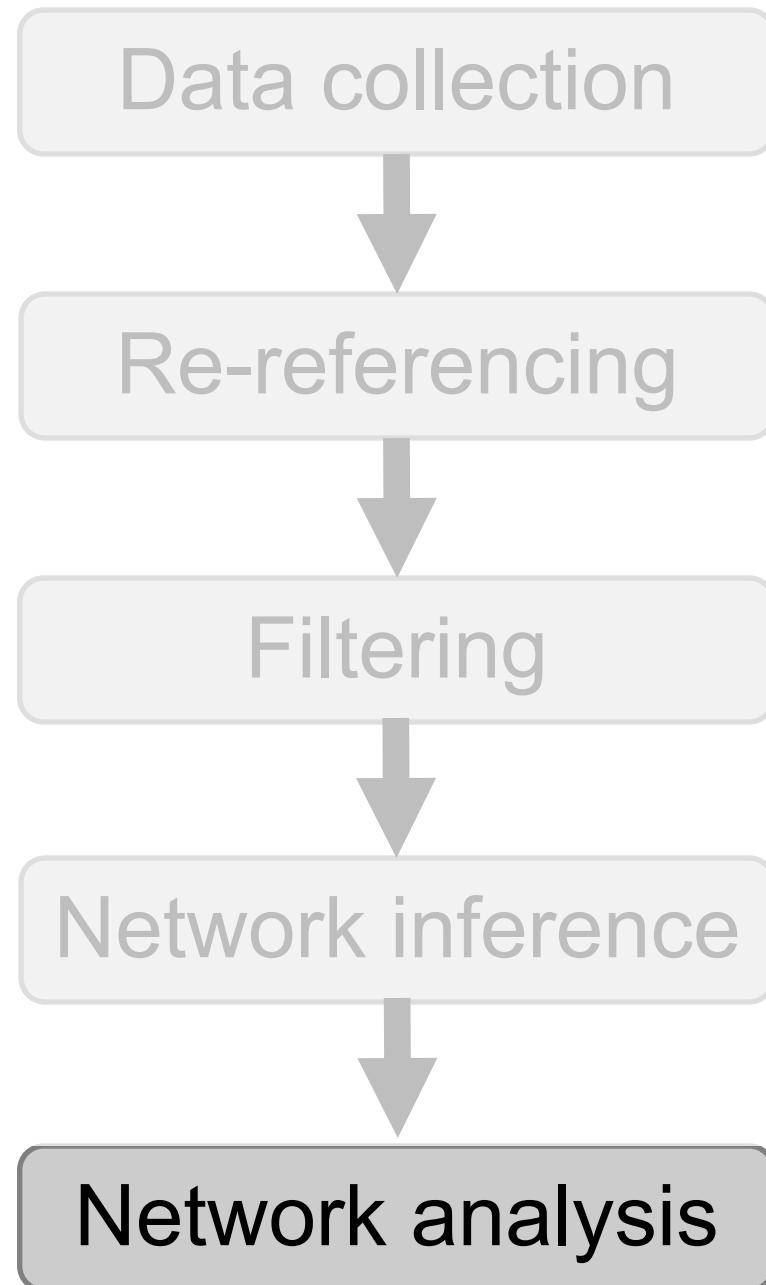
Binary



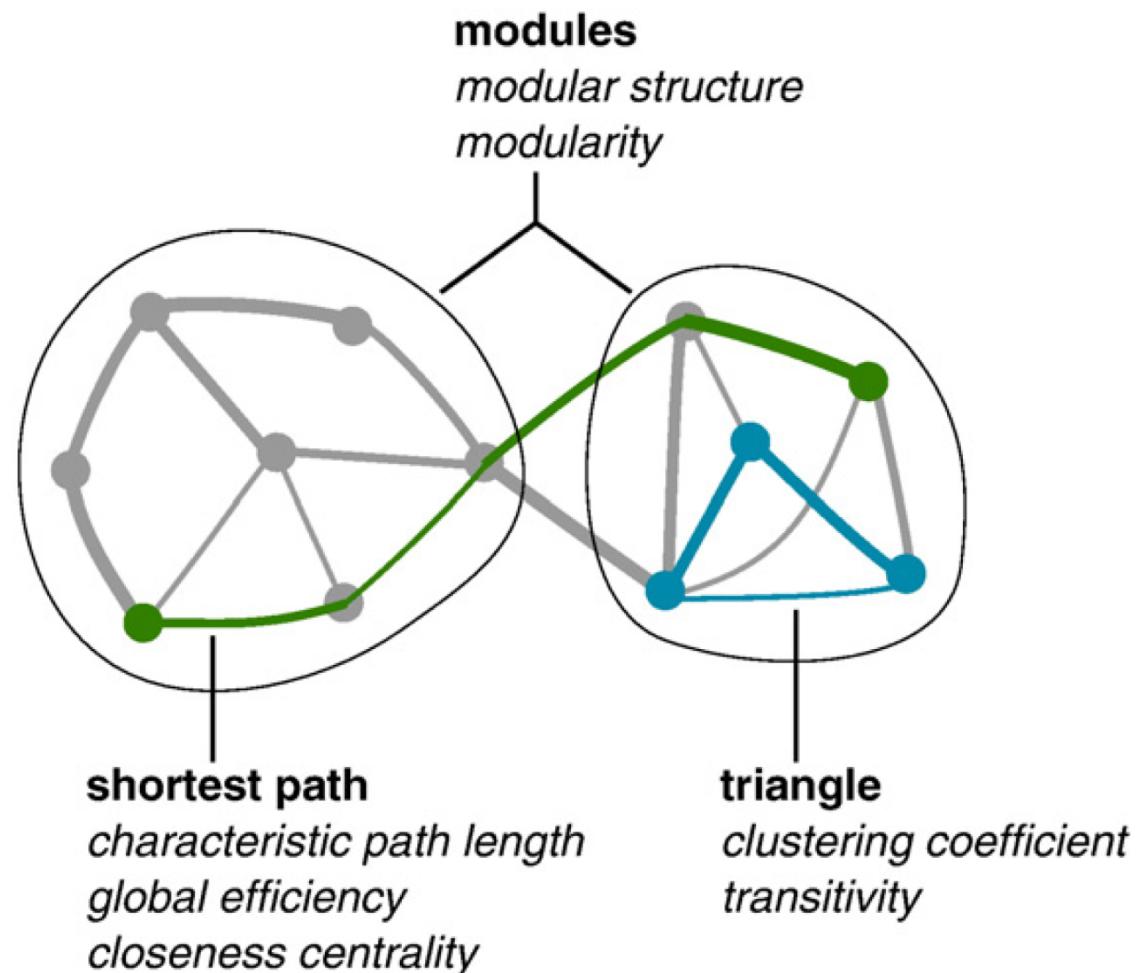
Threshold:

- Coupling measure
- p-value

Pipeline

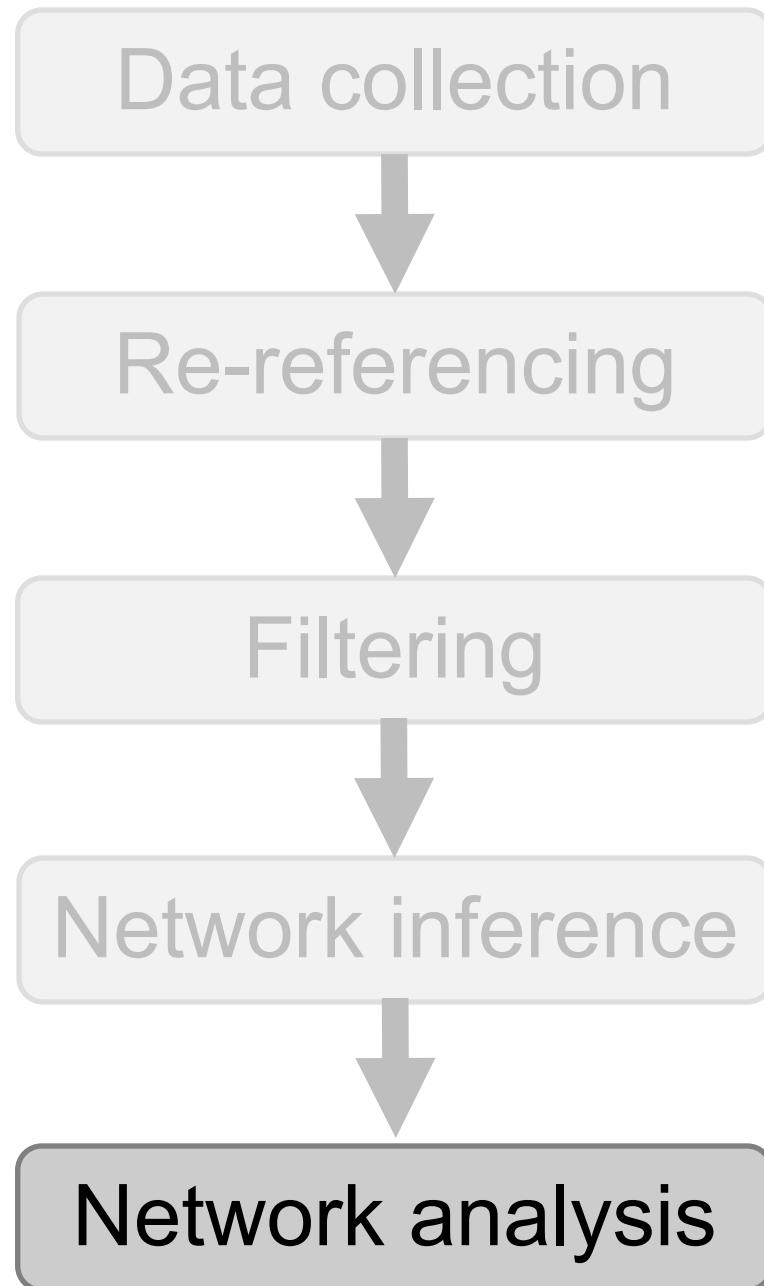


- Static network measures

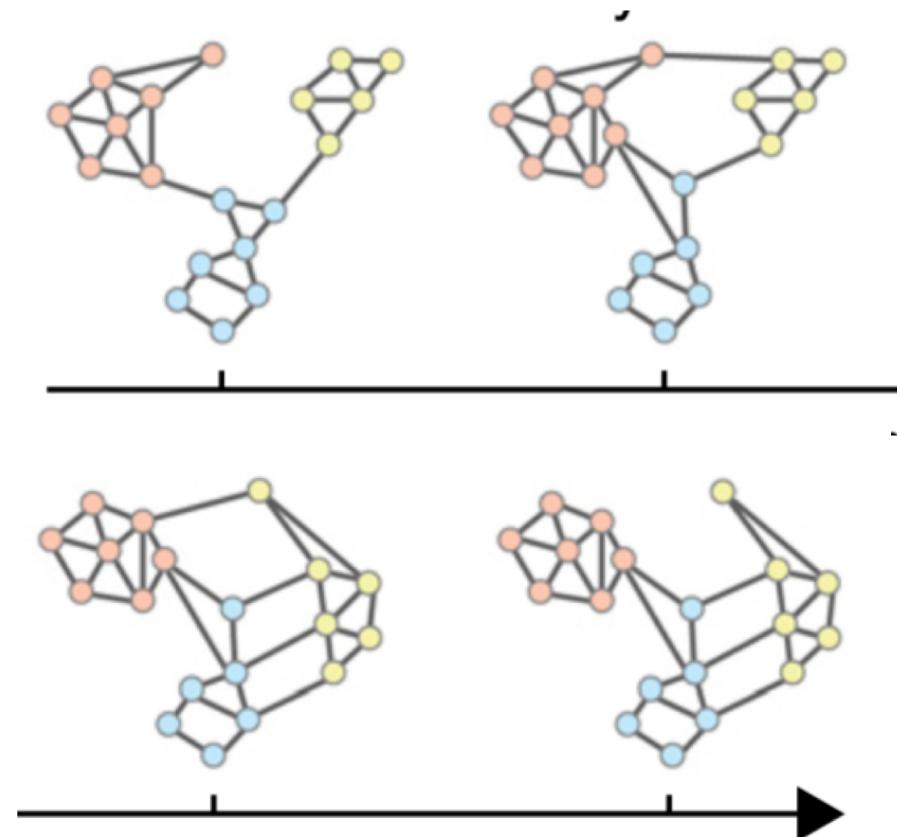


[Rubinov & Sporns, 2010]

Pipeline

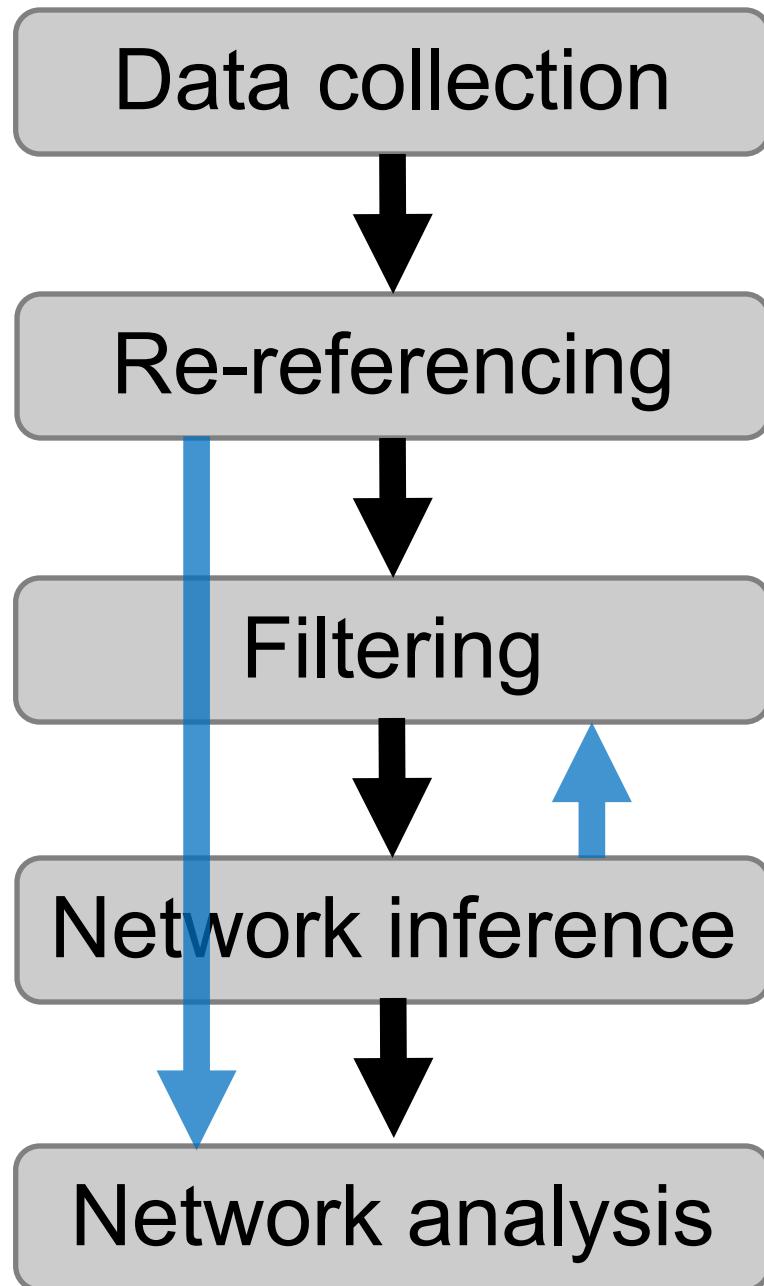


- Dynamic network measures



[Bassett & Sporns, 2017]

Pipeline

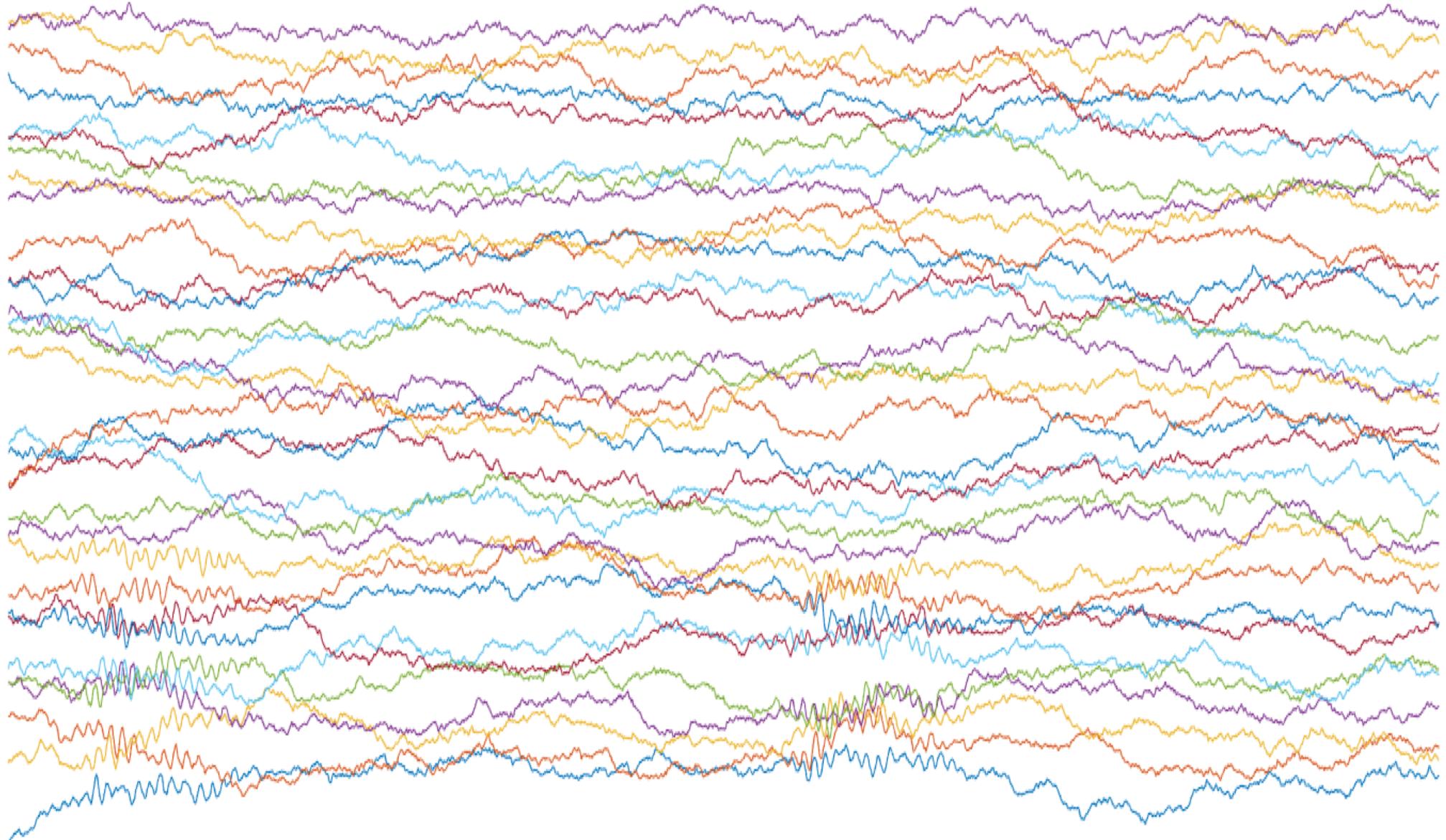


are interconnected ...

Reference choice impacts
network result.
... common average reference.

Network inference method
may impact filtering choice
... coherence in a specific band.

Implement the pipeline in an example ...



Example

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

Sleep-Networks-2021

An Introduction to Network Analysis & EEG Interpretation

This repository includes an example data set

`Example_sleep_data.mat`

and an example script to analyze these data

`Example_sleep_data_analysis.m`

Open the script and run it to implement specific choices for this data analysis pipeline:

```
graph TD; A[Data collection] --> B[Re-referencing]; B --> C[Filtering]; C --> D[Network inference]; D --> E[Network analysis]
```

The pipeline begins with a multielectrode recording and ends with a functional network. The pipeline is described in more detail in this presentation at the [Virtual Seminar Series: Computational Approaches to Signal Processing for Sleep](#).

The analysis pipeline illustrates one example approach. There are many others.

Example

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

%% Step 1a. Data collection -----

```
load('Example_sleep_data.mat')  
  
figure(); eeg_plot(t,d,'')  
title('EEG data'); xlabel('Time  
s')
```

```
% Load the data  
% d = the data [ time, electrodes ]  
% t = the time axis, in units of seconds.  
% detections = spindle detections [time, electrodes]  
% It's always a good idea to look at the raw data.
```

%% Step 1b. Spectrogram -----

```
%  
%  
simple_spectrogram(d(:,1),t);
```

```
% Make spectrogram for 1st electrode.
```

%% Step 2. Re-referencing -----

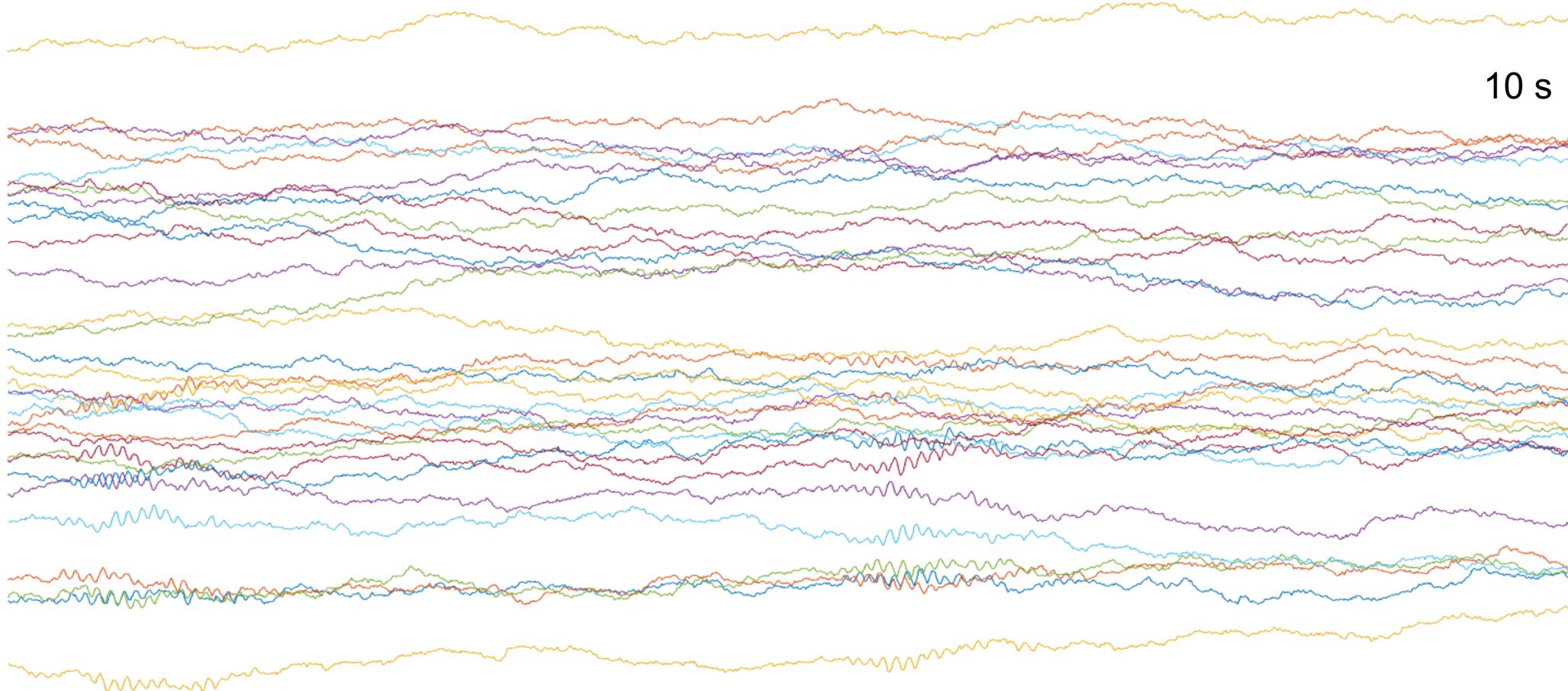
```
%  
% N/A
```

see [code](#)

Example

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

Motivated by work with Dr. Catherine Chu (Harvard/MGH) & Elizabeth Spencer (BU)



EEG, 32 channels, 256 Hz

Observations (rhythms)?
Coupling?

Example

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

```
%% Step 1a. Data collection -----  
  
load('Example_sleep_data.mat') % Load the data  
% d = the data [ time, electrodes ]  
% t = the time axis, in units of seconds.  
% detections = spindle detections [time, electrodes]  
figure(); eeg_plot(t,d,'') % It's always a good idea to look at the raw data.  
title('EEG data'); xlabel('Time [s]')
```

```
%% Step 1b. Spectrogram -----
```

```
%  
% simple_spectrogram(d(:,1),t); % Make spectrogram for 1st electrode.
```

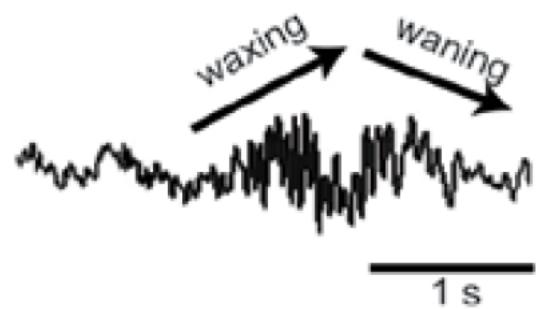
see [code](#)

Example

Rhythms?

- transient 0.5 – 2 s
- 9-16 Hz

spindles

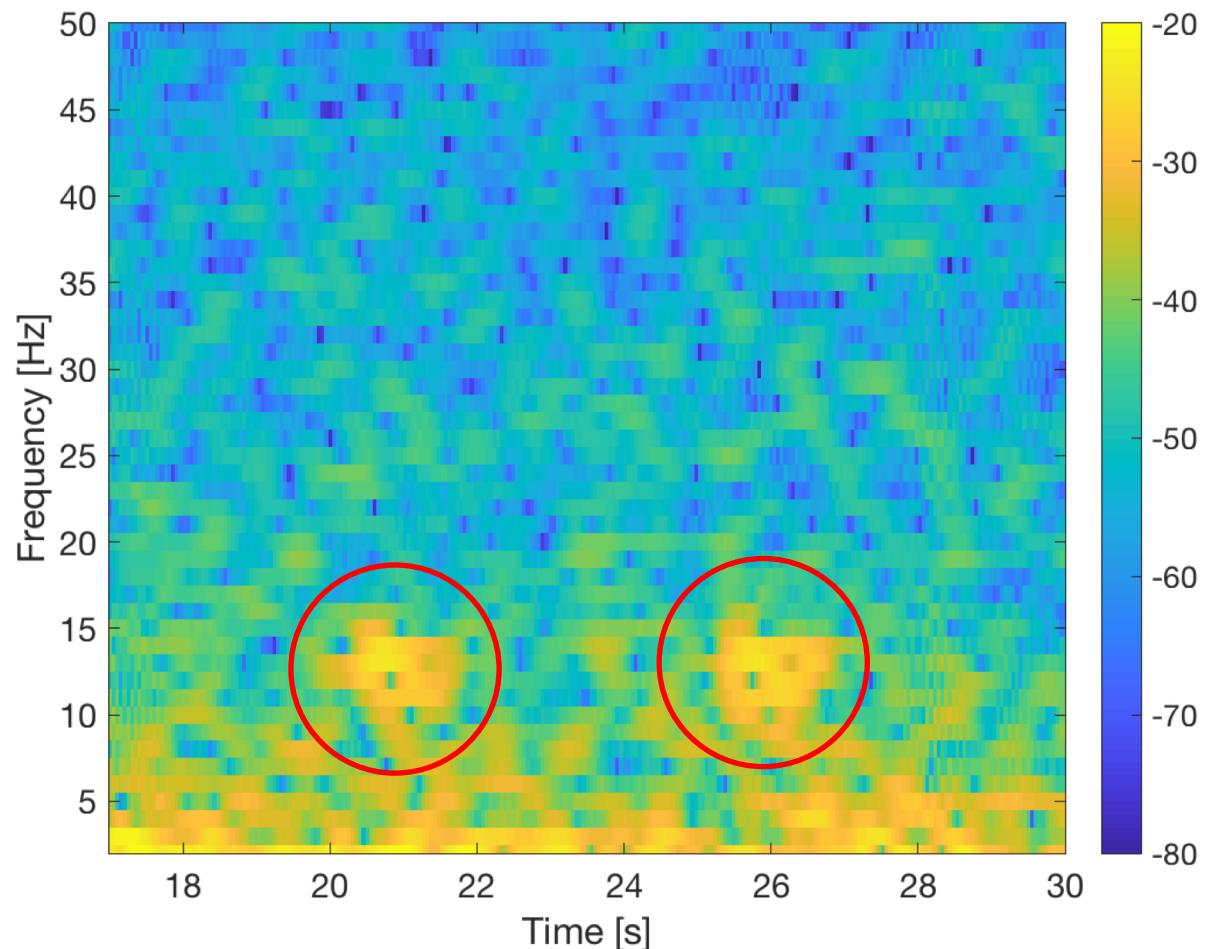


[Lüthi, Neuroscientist, 2014]

Network inference

... for rhythmic data?

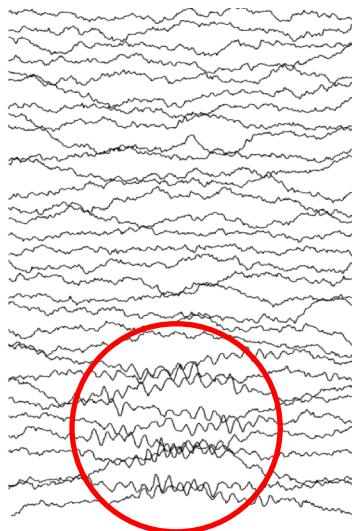
coherence makes sense ...



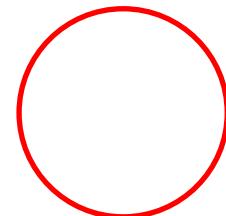
[Wamsley et al., Biological Psychiatry, 2012;
Ngo et al., eLife, 2020]

Example

Coherence Treat each spindle epoch as a trial:



spindle epoch



spindle epoch

Ask: between two electrodes, is there a constant phase relationship at 9-16 Hz across trials (i.e., when spindles occur)?

Guess?

Example

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

%% Step 2. Re-referencing -----

%
% N/A

%% Step 3. Filtering -----

%
% N/A

%% Step 4. Network inference -----

%
% Infer the functional connectivity,
[C] = infer_network_coherence(t,d,detections);
figure(); pcolor(C); caxis([0,1]) % ... and visualize it.
xlabel('Node number'); ylabel('Node number'); title('Coherence (9-16 Hz)')

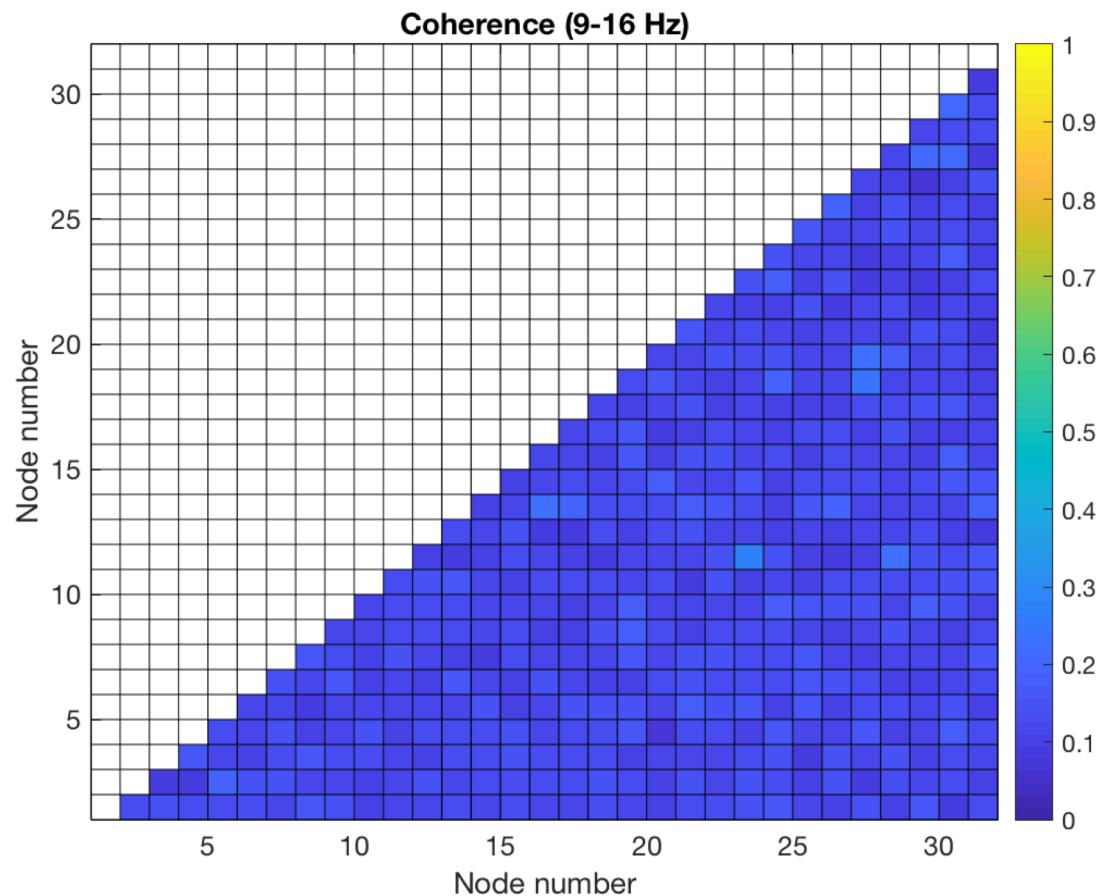
see [code](#)

Example

Coherence

1 = strong coherence
0 = weak coherence

Adjacency matrix



Conclusion:

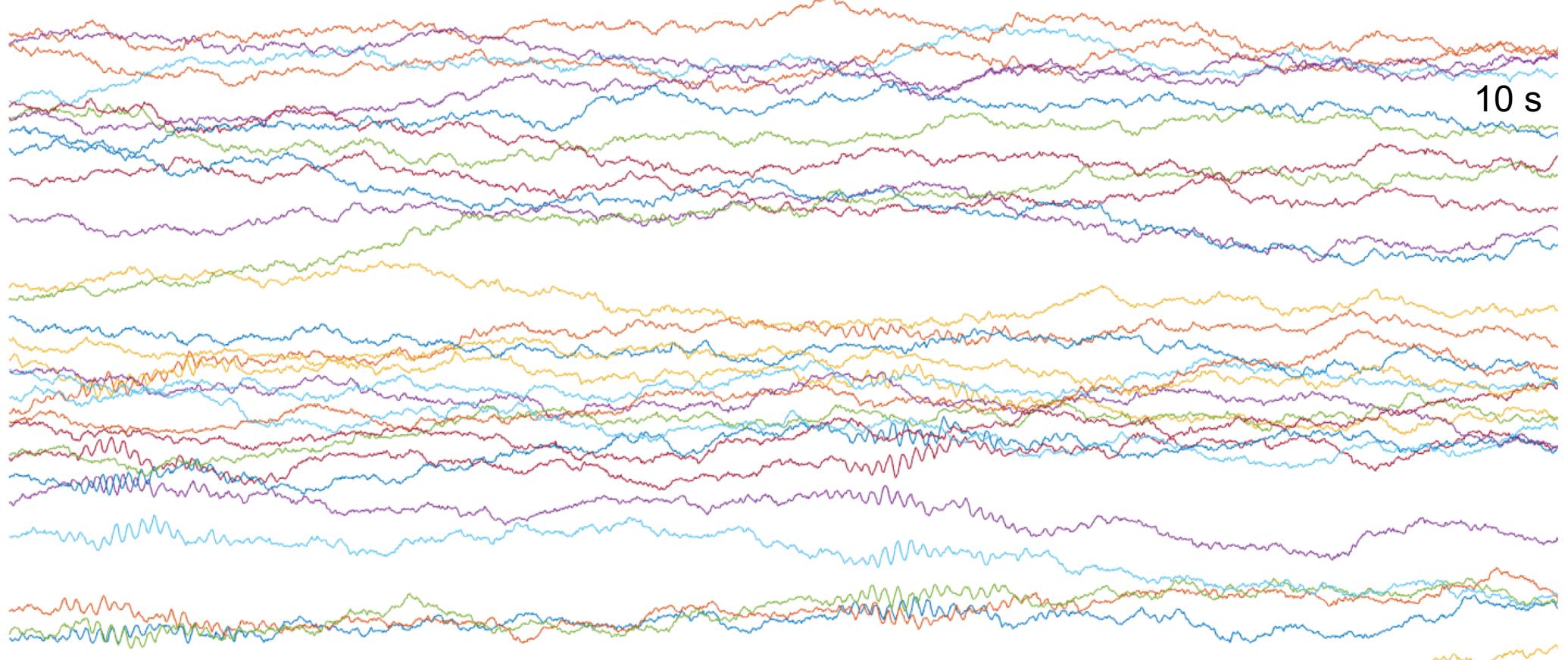
No evidence of coherence?

Example

Coherence

Result: no coherence

Remember visual inspection



Does this result make sense?

Example

Coherence

Result: no coherence

Confusing ...

Why?

1) Our spindle detector is bad?

Let's look ...

Example

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

%% TRY AGAIN ...

%% Step 3. Filter & visualize spindle detections

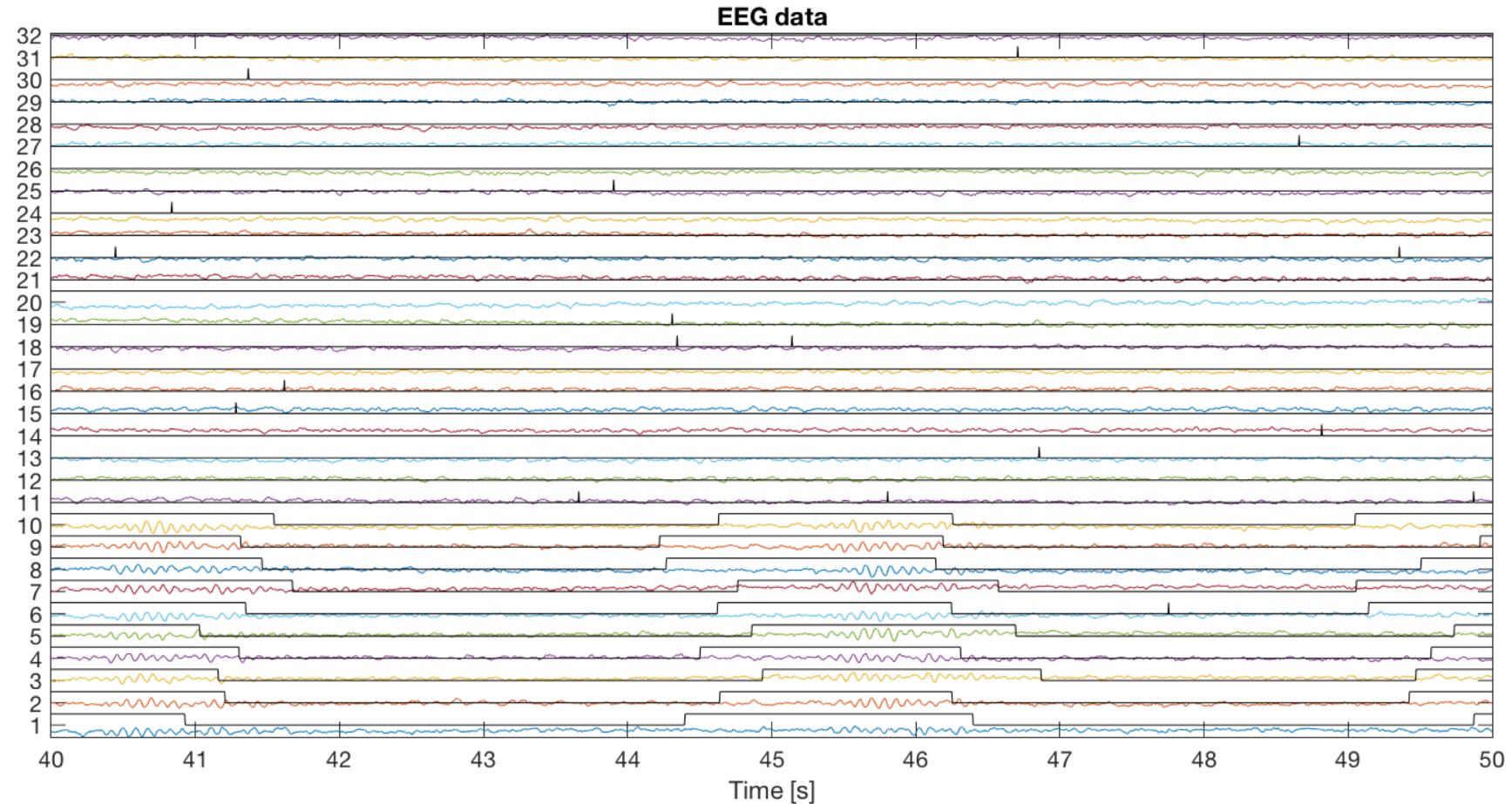
```
%  
%  
Wn = [2,50]; % Choose filter range from [1,50] Hz,  
d_filtered = simple_filter(t,d,Wn); % ... apply the filter,  
figure(); eeg_plot(t,d_filtered,''); hold on; eeg_plot(t,detections,'k'); hold off  
title('EEG data'); xlabel 'Time [s]'
```



see [code](#)

Example

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>



What do you think of the detector?

Example

Coherence

Result: no coherence

Why?

~~1) Our spindle detector is bad?~~ No

Visual inspection suggests spindle detector ok.

[Wamsley et al, Biol Psych, 2012; Warby et al., Nature Methods, 2014; Kramer et al., J Neurosci, 2021]

What else?

Example

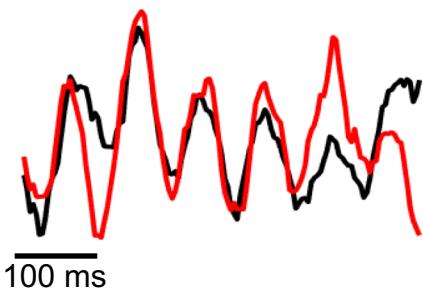
Coherence

Result: no coherence

Why?

Consider spindle epochs at 2 electrodes:

trial₁



spindles: in phase

phase shifted

phase shifted

out of phase

Conclusion: between these 2 electrodes, no evidence of a constant phase relationship across spindle epochs (trials).

Coherence ≈ 0

Example

initial plan

Network inference

... for rhythmic data?

coherence makes sense.

spindles are not coherent.

Phase relationship between spindles?

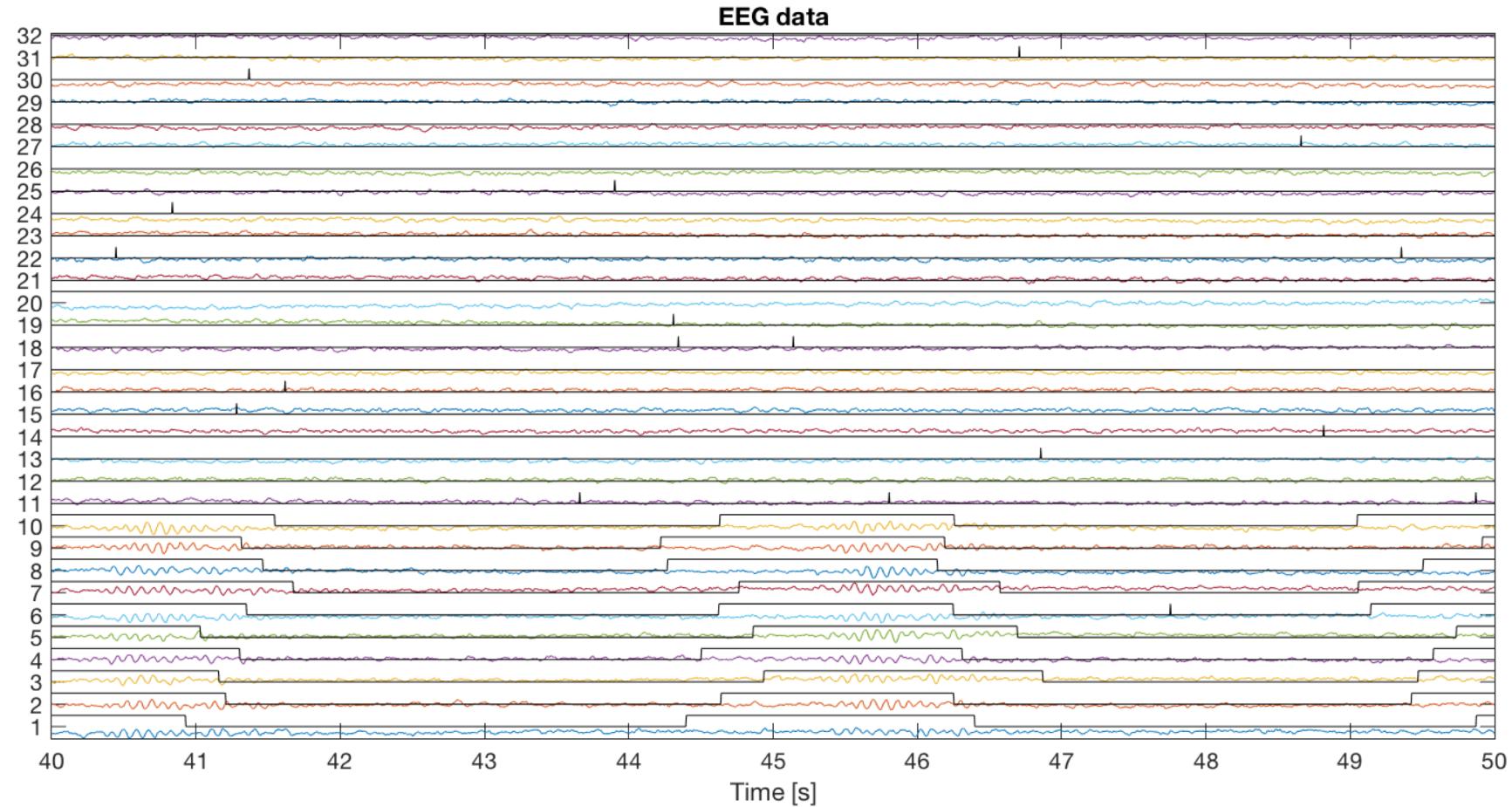
... fine temporal structure

Interesting, but maybe there's more?

Consider ...

Example

Look at the data (again)

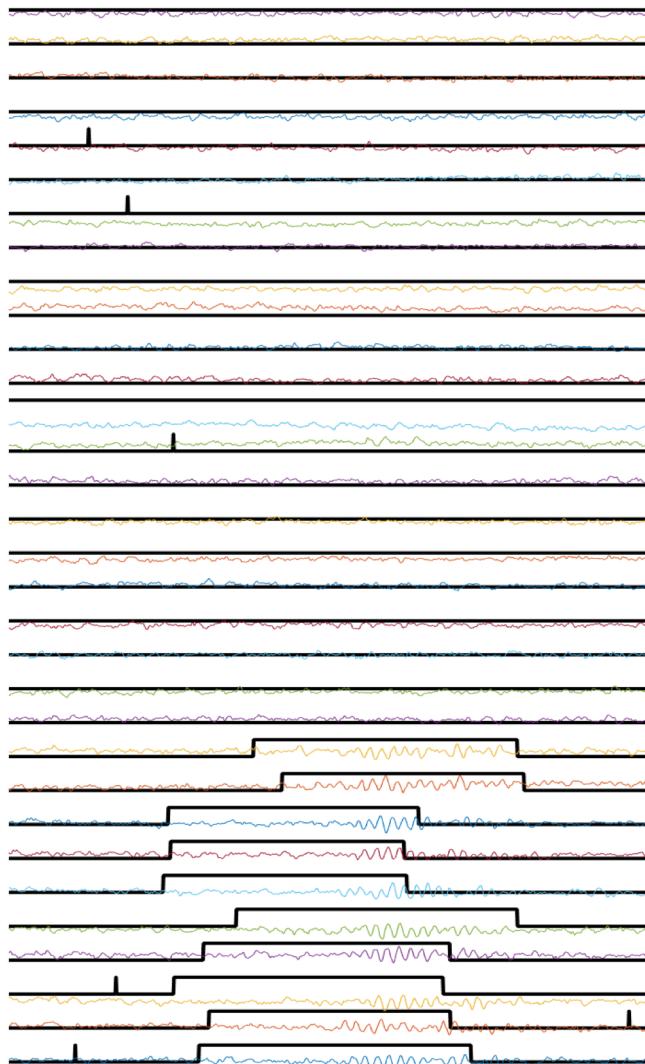


What stands out: detections overlap across electrodes

Instead of coupling in voltages, coupling of detections?

Example

Network inference

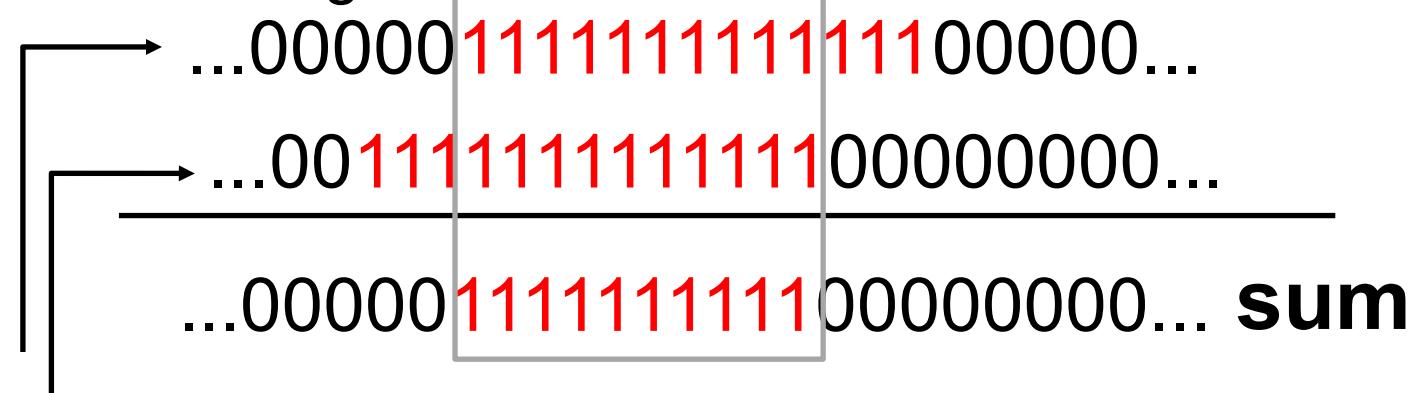


... do spindles occur at the same time?

Compute coincidence

When detections overlap,
product = 1

detection signal



= big number,
when many detections overlap

Example

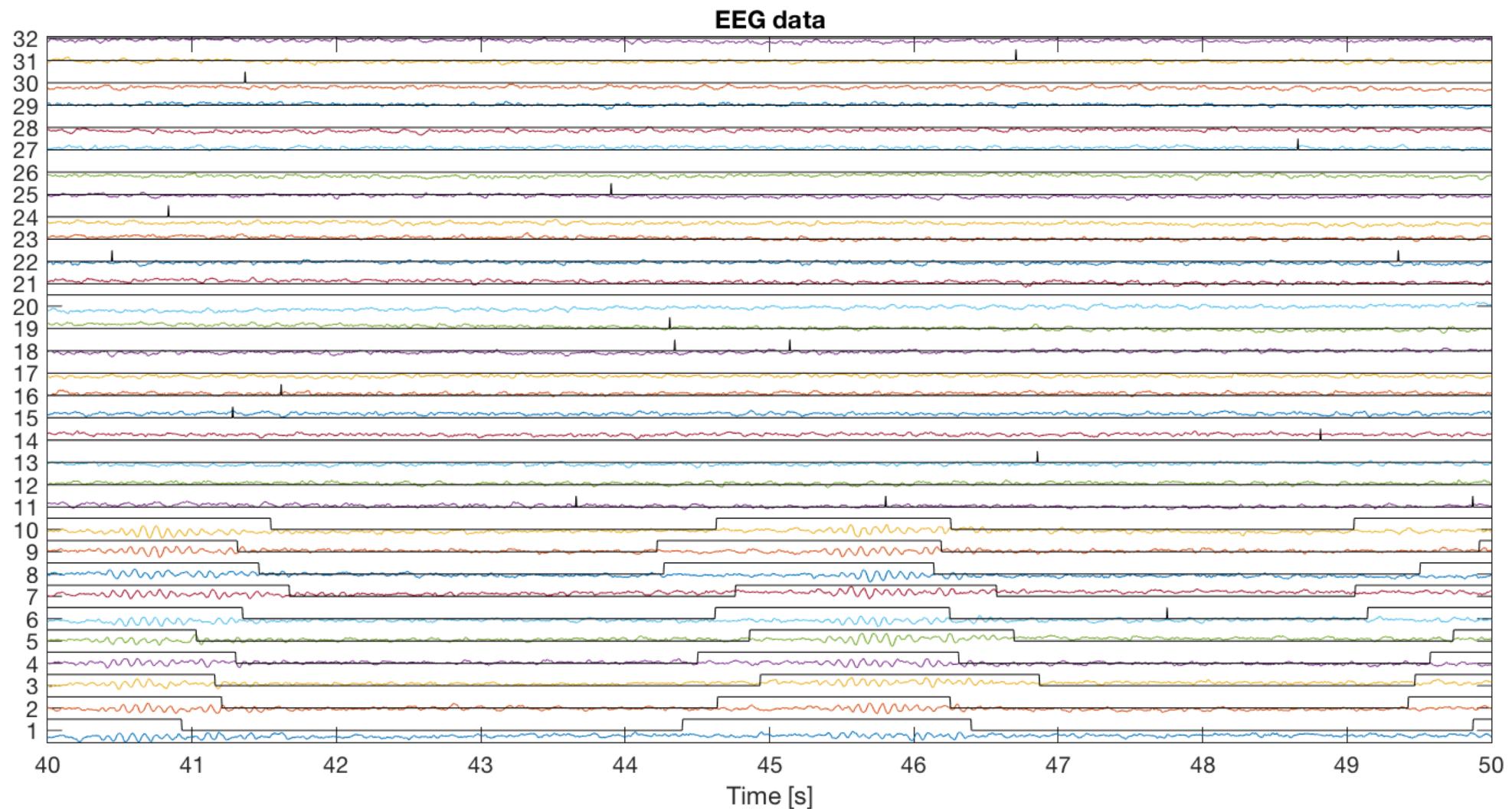
<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

```
%% Step 4. Network inference -----  
%  
% % Infer the functional connectivity,  
[C] = infer_network_coincidence(t,d,detections);  
figure(); pcolor(C); colorbar; % ... and visualize it.  
xlabel('Node number'); ylabel('Node number'); title('Coincidence')
```

see [code](#)

Example

Which electrodes do you expect to be coincident?



Example

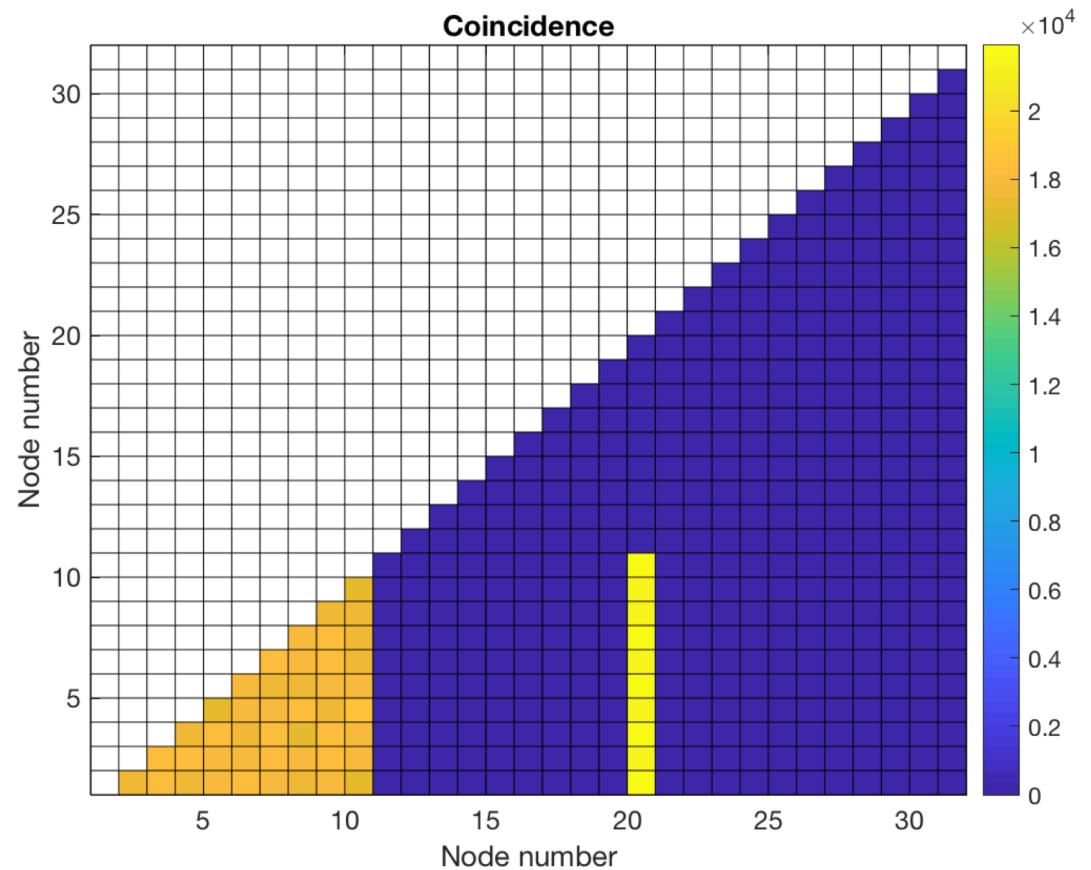
Compute coincidence

Conclusion:

Evidence of coincidence

1-10 coincident

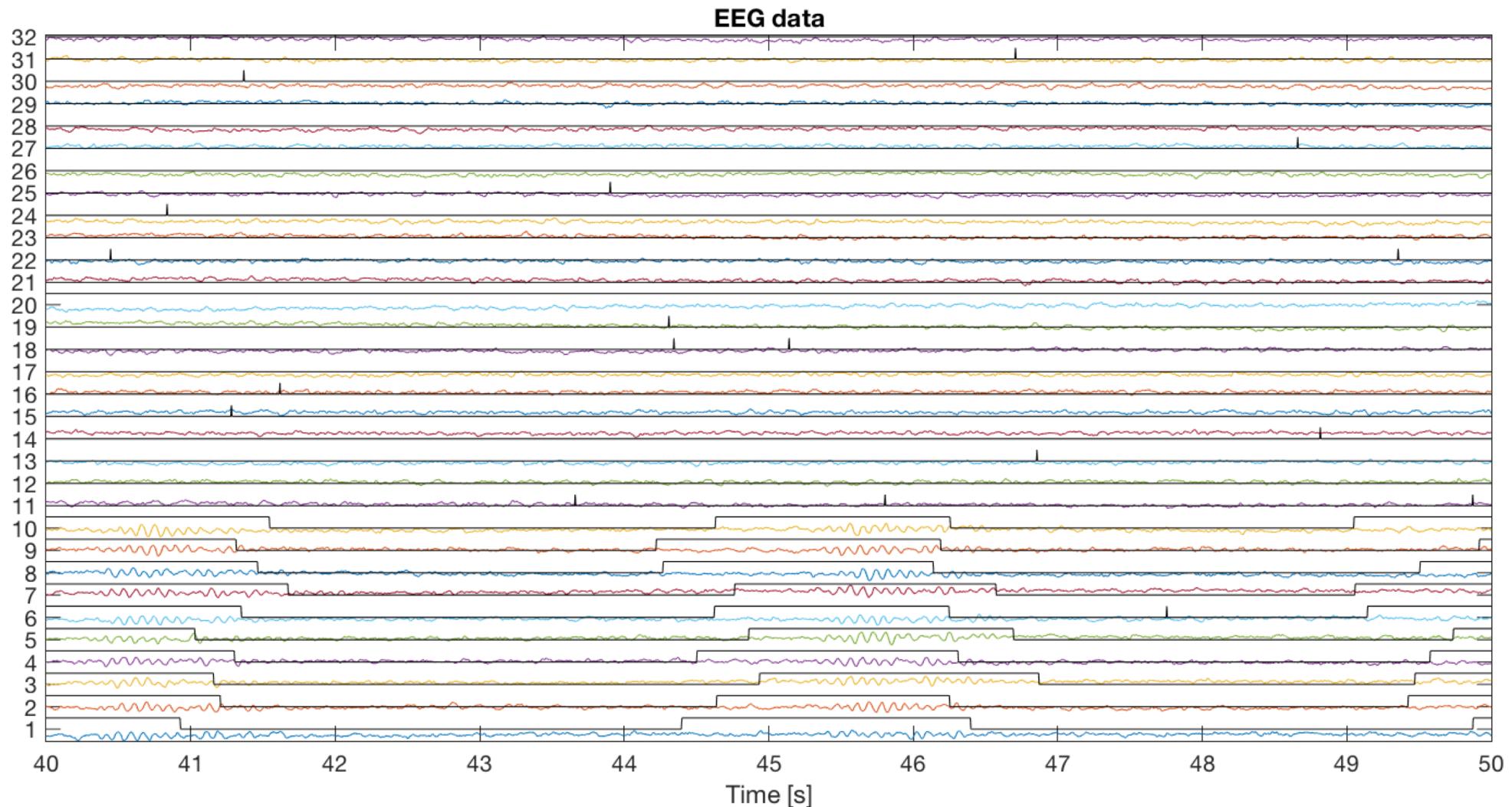
20? coincident



That's interesting there's a problem?

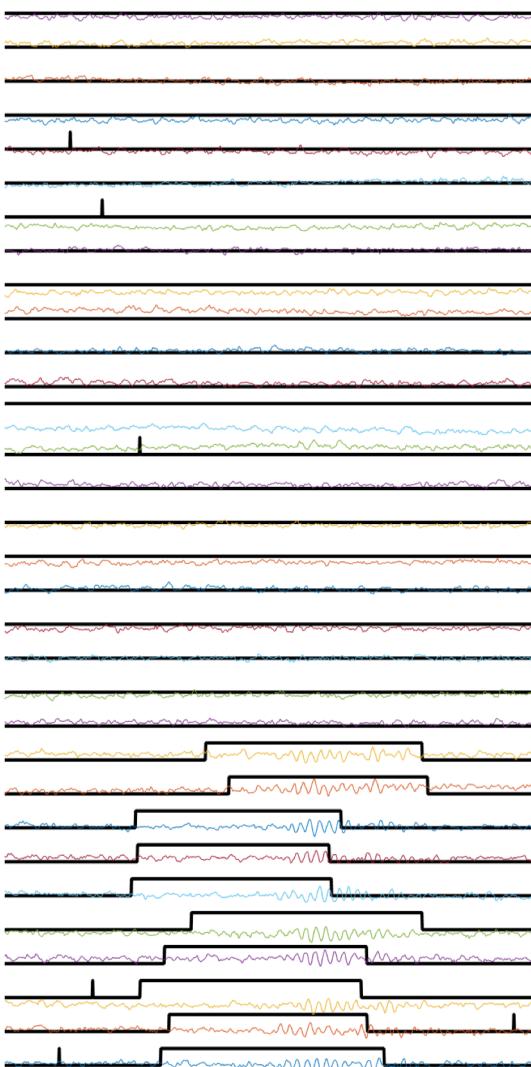
Example

It's here, but very subtle ...

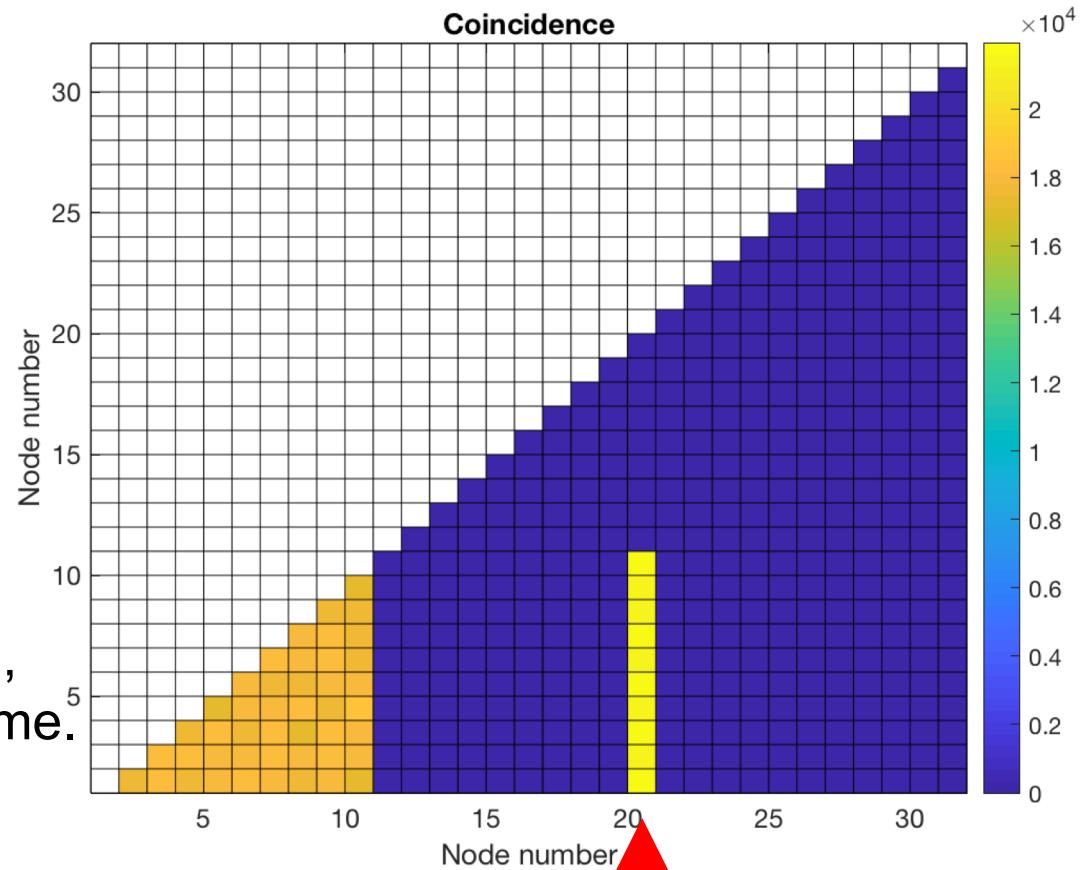


Example

Problem coincidence



Detector says:
at electrode 20,
spindle at all time.



High detection rate = high coincidence

Example: sleep spindles

Solution scaled coincidence

$$\begin{array}{rcl} \dots00000\textcolor{red}{11111111111111}00000\dots & \text{sum} = s_1 \\ \dots00\textcolor{red}{11111111111111}00000000\dots & \text{sum} = s_2 \\ \hline \dots00000\textcolor{red}{1111111111}00000000\dots & \text{sum} = s_{12} \end{array}$$

$$\text{scaled coincidence} = s_{12} / (s_1 s_2)$$



scale by detection rate at each electrode

Rate impacts coupling measures [Cohen & Kohn, Nat Neuro, 2011;
Lepage et al., Neural Comp, 2011]

Example

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

%% TRY AGAIN ...

%% Step 4. Network inference -----

```
%  
% % Infer the functional connectivity,  
[C] = infer_network_coincidence_scaled(t,d,detections);  
figure(); pcolor(C); colorbar; % ... and visualize it.  
xlabel('Node number'); ylabel('Node number'); title('Coincidence scaled')
```



see [code](#)

Example

Compute scaled coincidence

Conclusion:

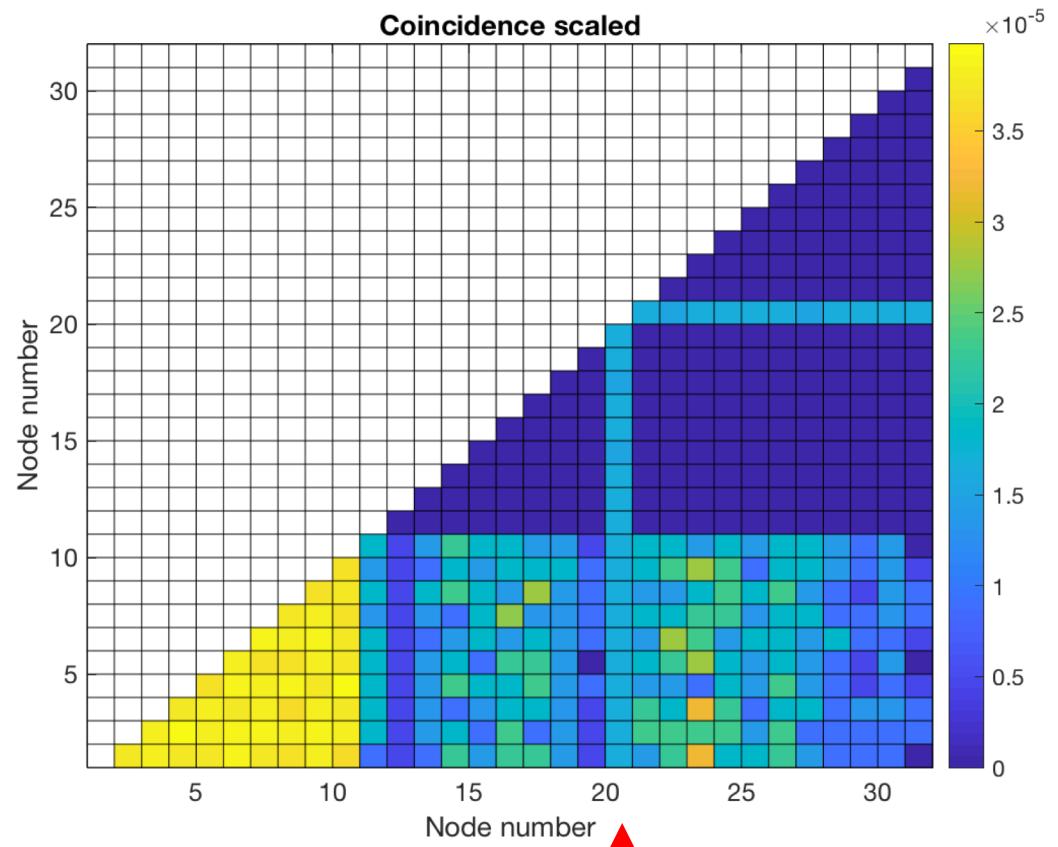
Evidence of coincidence

1-10 coincident

20? coincident

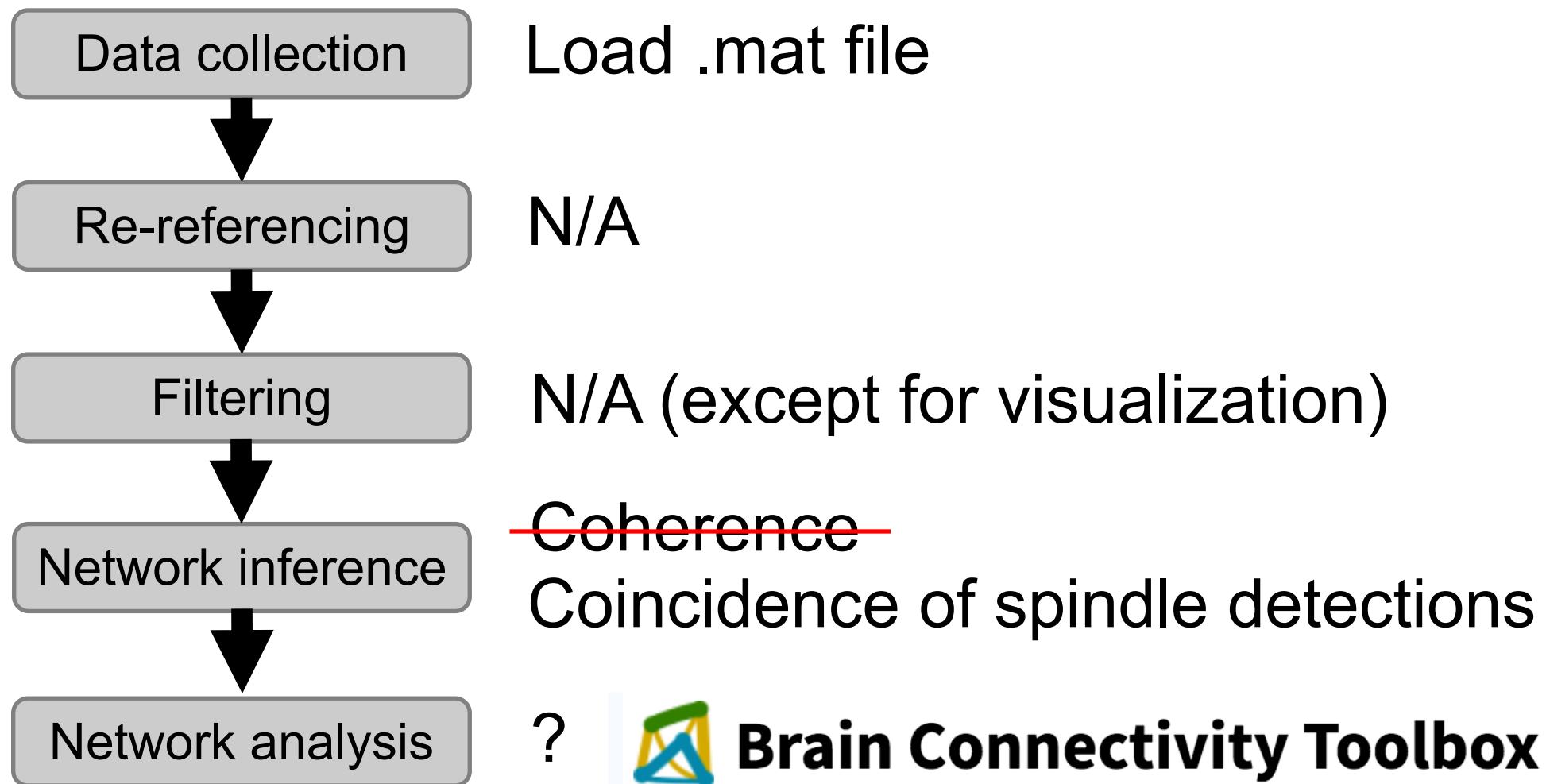
Network inference

Problem solved?



Conclusions

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>



Conclusions

Characterizing functional connectivity in the brain is:

... filled with pitfalls.

... requires careful decisions & interpretation.

... can be useful.

Thank you

Dr. Prerau, organizer, Computational Approaches to Signal Processing for Sleep

Elizabeth Spencer, Uri Eden, Boston University, USA

Catherine Chu, Mass General Hospital / Harvard University, USA

<https://github.com/Mark-Kramer/Sleep-Networks-2021/>

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NIH R01NS115868

NIH R01EB026938