# Brain connectivity analysis from neural data SINC2 one-day workshop

Adrià Tauste-Campo Andrea Insabato Matthieu Gilson

Toy models: http://github.com/cns-upf

Wifi: event@upf.edu Password: 7fabrauni



#### **Outline**

- Introduction
  - Define scientific question and context
  - Roadmap for connectivity measures
  - Value of model
- Linear analysis
  - Spectrum and statistical testing (null model)
  - Connectivity estimation in network (PC, MVAR)
- Non-linear analysis
  - Probabilistic modeling
  - Connectivity estimation using information-theoretic measures
- Machine learning
  - ML as an alternative to hypothesis testing
  - Classification
  - Evaluation of classifiers

- Time will judge the validity of theories, models, etc.
- Replicability crisis

#### Reproducibility in Science Improving the Standard for Basic and Preclinical Research

C. Glenn Begley, John P.A. Ioannidis

Abstract: Medical and scientific advances are predicated on new knowledge that is robust and reliable and that serves as a solid foundation on which further advances can be built. In biomedical research, we are in the midst of a revolution with the generation of new data and scientific publications at a previously unprecedented rate. However, unfortunately, there is compelling evidence that the majority of these discoveries will not stand the test of time. To a large extent, this reproducibility crisis in basic and preclinical research may be as a result of failure to adhere to good scientific practice and the desperation to publish or perish. This is a multifaceted, multistakeholder problem. No single party is solely responsible, and no single solution will suffice. Here we review the reproducibility problems in basic and preclinical biomedical research, highlight some of the complexities, and discuss potential solutions that may help improve research quality and reproducibility. (Circ Res. 2015;116:116-126. DOI: 10.1161/CIRCRESAHA.114.303819.)

**Key Words:** funding ■ journals ■ research integrity ■ universities

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- Measures on biological signals and interpretation:
  - Where is information?
  - Validation, Robustness
  - Simplicity

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- Back to reality: limited data, uncontrolled (mixed) sources of noise, issues with stationarity of protocols/conditions

#### Roadmap / Typology

**Partial** Granger Transfer correlations causality entropy analysis Multivariate autoregressive Power (MVAR) model spectrum Coherence Phase Phase locking Pearson **Partial** lag index value correlation coherence (functional connectivity)

# Roadmap / Typology

	Without time	Linear in time domain	Linear in frequency domain	Non-linear
Nodal measure	Variance	Auto- covariance	Power spectrum	
Connectivity measures	Pearson correlation	Cross- covariances	Coherence	Phase locking value index
and estimates	Partial correlations	MVAR Partial coherence Granger causality analysis		Transfer entropy

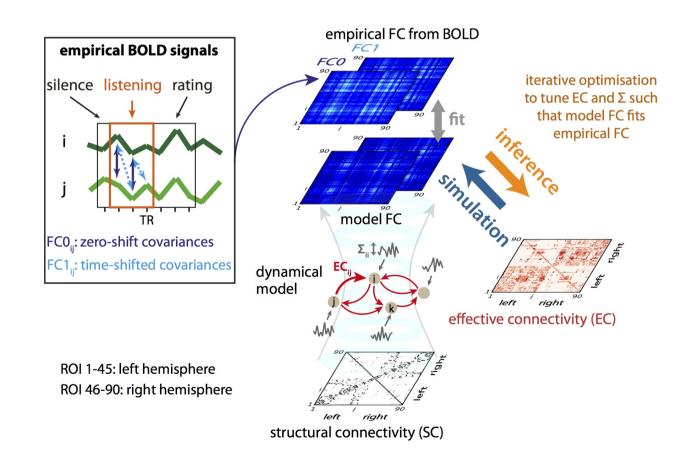
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There is always a model behind a measure (especially to interpret the values it takes), so better know the details about it!

#### How to use a model?

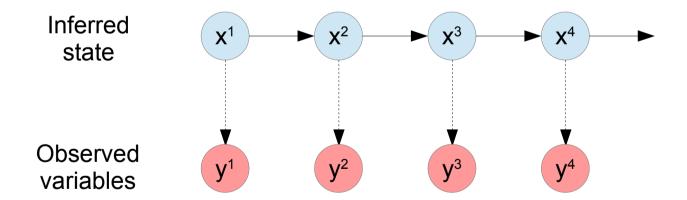
- Exploration of concepts (qualitative approach)
- Fit and interpretation of data (quantitative approach)



#### How to use a model?

- Exploration of concepts (qualitative approach)
- Fit and interpretation of data (quantitative approach): investigate latent variables

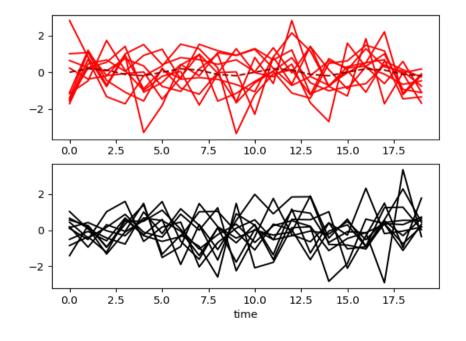
#### Hidden Markov model



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- http://github.com/cns-upf/test\_modulation.py.ipynb
- Single time series for n subjects (behavioral data, electrophysiology, etc.)
- Is there a modulation in signal common to all subjects?

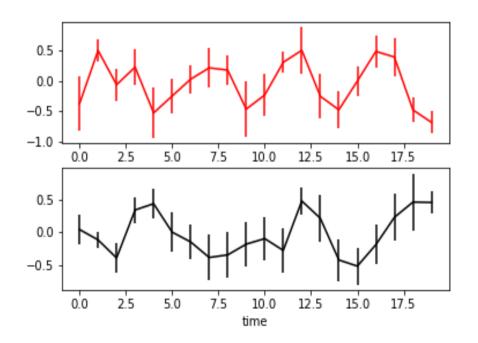


#### Here:

- n\_sub = 10 subjects
- Weak amplitude a = 0.2

Random (white noise)

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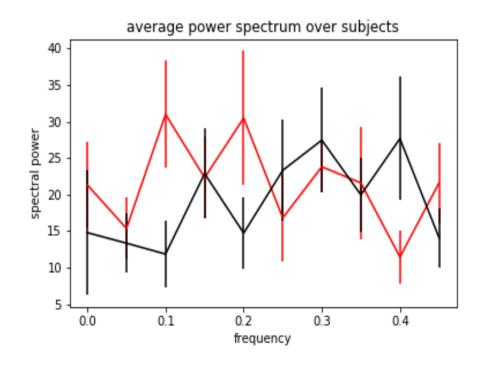


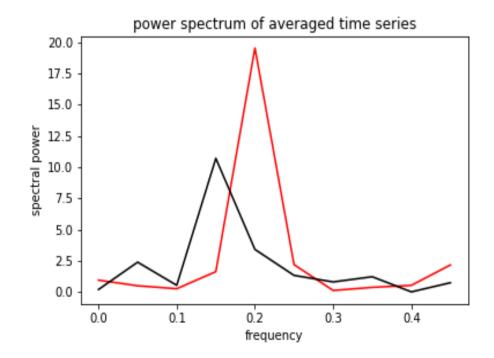
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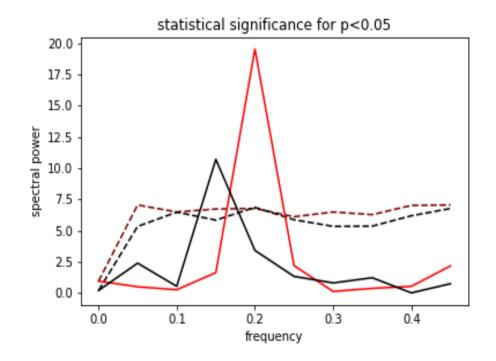
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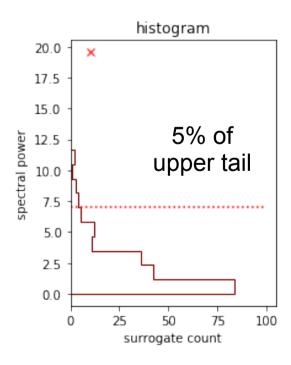
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- Power spectrum to investigate rhythms
- Average before or after Fourier transform?



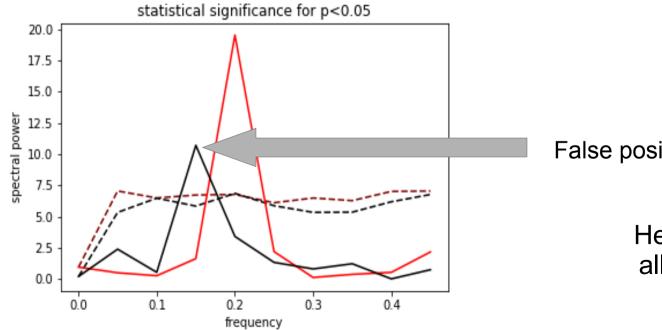


- http://github.com/cns-upf/test\_modulation.py.ipynb
- Significance test for spectrum of average time series
- Generate surrogates by shuffling data for each subject (then averaging...)





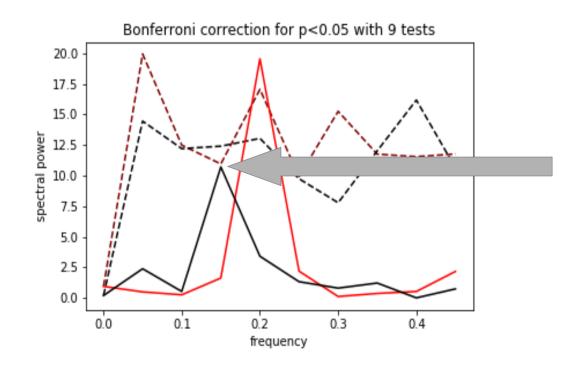
- http://github.com/cns-upf/test\_modulation.py.ipynb
- Define threshold for multiple comparisons?



False positive (5% allowed here)

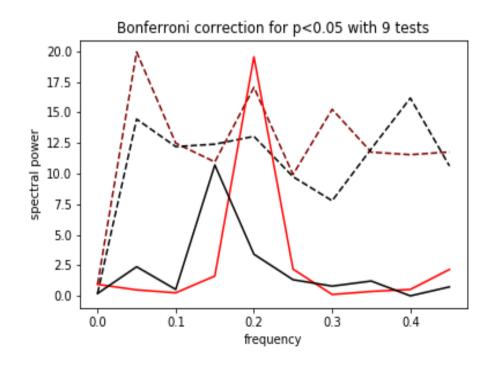
Here 9 tests for all frequencies

- http://github.com/cns-upf/test\_modulation.py.ipynb
- Bonferroni correction (conservative threshold)
- Assuming independent tests for all 9 frequencies



p-value = 0.05 / 9 = 0.0056

- http://github.com/cns-upf/test\_modulation.py.ipynb
- What is your question?
  - Is there a modulation at any frequency?
  - Do you want to test for a specific frequency?



#### Play with:

- signal duration T
- modulation amplitude a
- number of subjects *n\_sub*
- number of surrogate n\_shuf
- surrogate type
- desired p-value pval

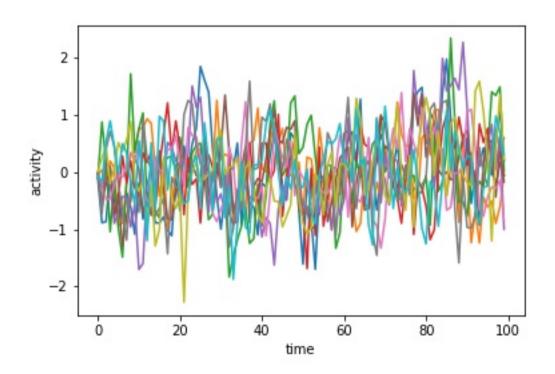
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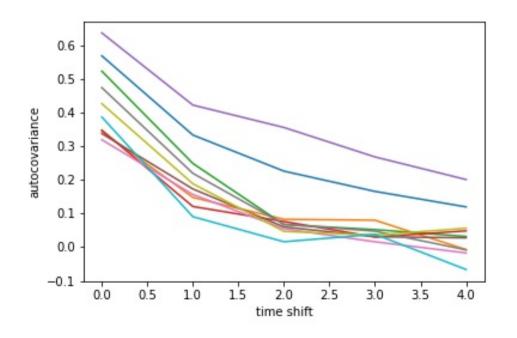
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- Stationarity? On which time scale?
- Does directionality matter?

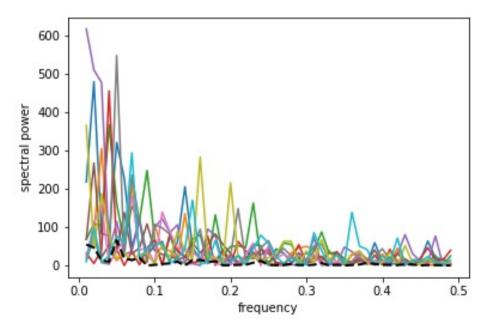
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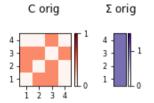
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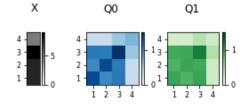
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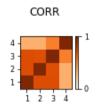
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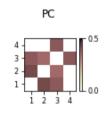
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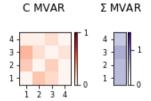
- http://github.com/cns-upf/estimate\_directed\_connectivity.ipynb
- Pearson correlation
- Partial correlation (related to graphical model)
- Multivariate autoregressive model (MVAR)
- Multivariate Ornstein-Uhlenbeck (MOU)

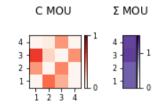


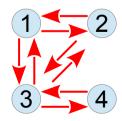










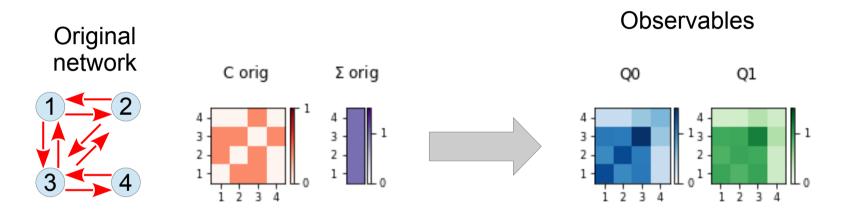


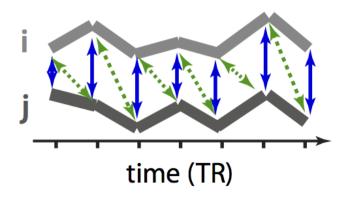
Signal generated using the MOU dynamics (continuous time), observations involve down-sampling

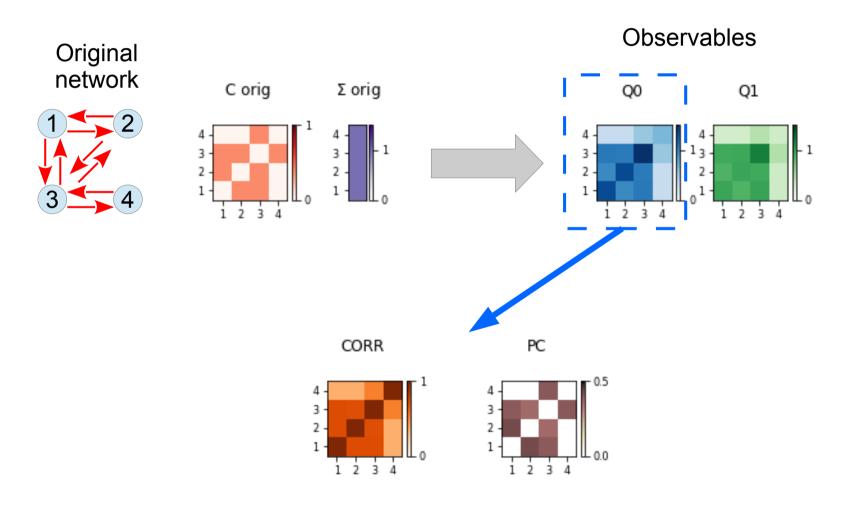
$$\mathsf{MVAR}$$

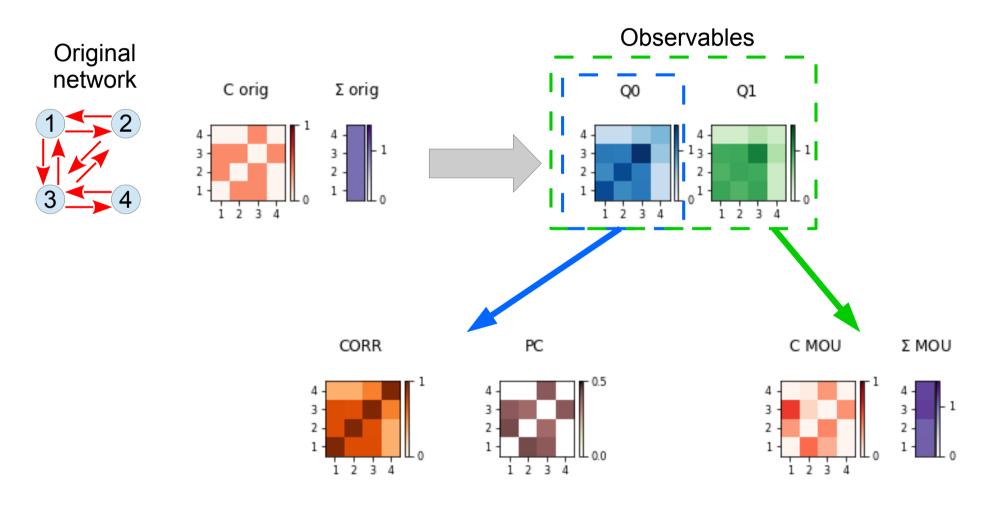
$$x^{t+1} = A x^t + \zeta$$

$$dx^{t} = J x^{t} dt + dW^{t}$$



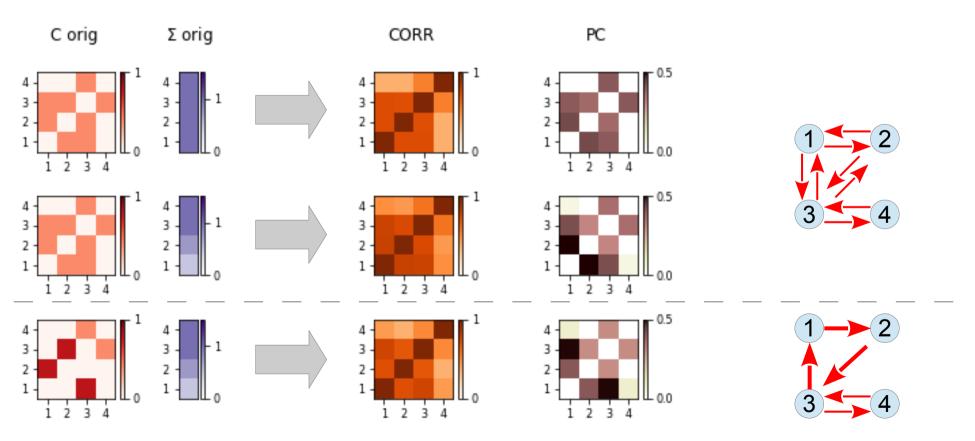


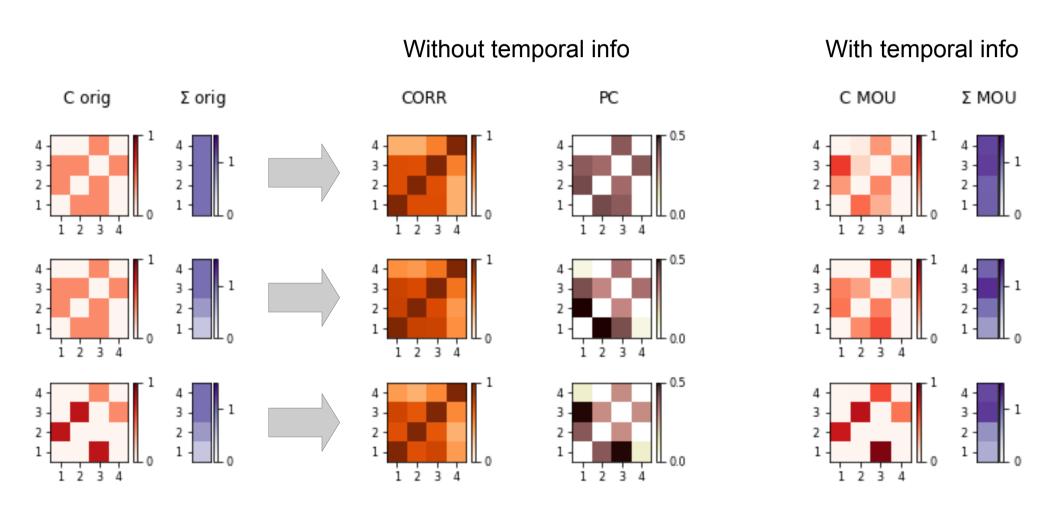




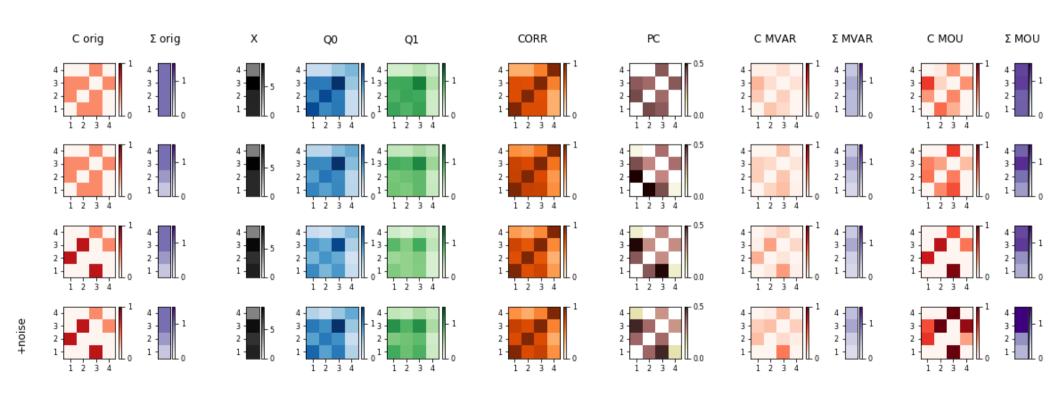
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#### Without temporal info





- http://github.com/cns-upf/estimate\_directed\_connectivity.ipynb
- Play with parameters of original network, observation noise, etc.



- Toy models: (http://github.com/cns-upf)
  - test\_modulation
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  - fMRI data: http://github.com/MatthieuGilson/WBLEC\_toolbox
- Linear formalism is often the only computationally-feasible approach for large networks (>20 nodes)
  - Spectral domain
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- Non-parametric testing to avoid assumption that observed signals are Gaussian
  - Statistical testing for MVAR using surrogates (Gilson, Tauste Campo et al. Net Neurosci 2017)
- Heterogeneous signals
  - behavioral data and neural signals (with distinct timescales)
- Multiple comparisons (N nodes → N² connections): What type of correction to apply?
   Independent tests?
  - Detection of effect for connection clusters instead of individual connections
  - Machine learning to measure effect size