

# Exploiting Lag-Time Information for Optimizing Network Inference

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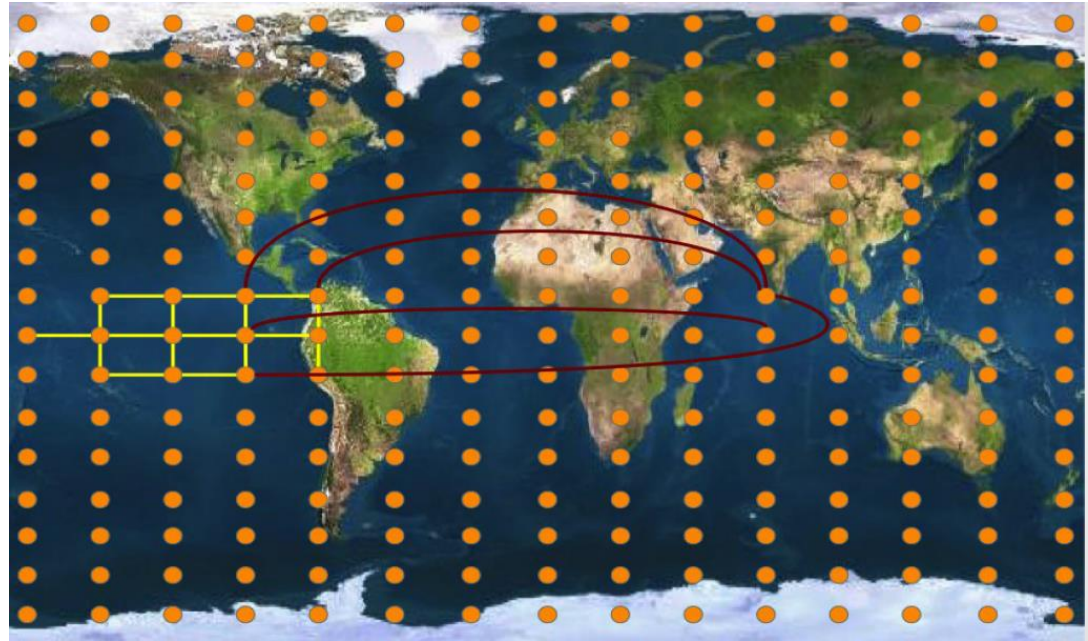


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# Motivation: how to infer the connectivity of a complex system from observed data?



Spatial grid points used for building climate networks

# Linear and nonlinear correlation analysis are used for inferring undirected links

Time series recorded at nodes  $i$  and  $j$ :  $a_i(t)$ ,  $a_j(t)$ ,  $t=1, \dots, T$

- Lagged cross correlation 
$$CC_{ij}(\tau_{ij}) = \frac{1}{T - \tau_{\max}} \left| \sum_{t=0}^{T-\tau_{\max}} a_i(t) a_j(t + \tau_{ij}) \right|$$
- Mutual information 
$$MI_{ij}(\tau_{ij}) = \sum_{m,n} p_{ij}(m, n) \log_2 \left( \frac{p_{ij}(m, n)}{p_i(m) p_j(n)} \right)$$
  - Histograms
  - Symbolic (ordinal) patterns

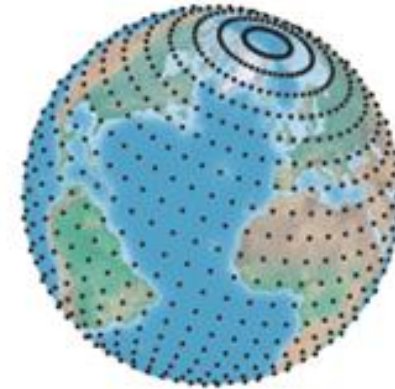
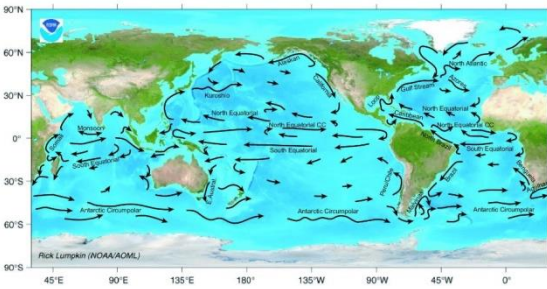
$p_i$  is the prob. that  $a_i(t)$  lies in bin  $i$   
 $p_j$  is the prob. that  $a_j(t+\tau_{ij})$  lies in bin  $j$

Statistical Similarity Measure (SSM): CC or MI

$$SSM_{ij} = \max_{\tau_{ij}} SSM_{ij}(\tau_{ij}) \quad \tau_{\max} = T/5$$

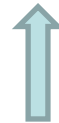
If **SSM**<sub>ij</sub> > **TH** the link  $i \longleftrightarrow j$  exists, otherwise, it does not exist.

# Complex network representation of the climate system

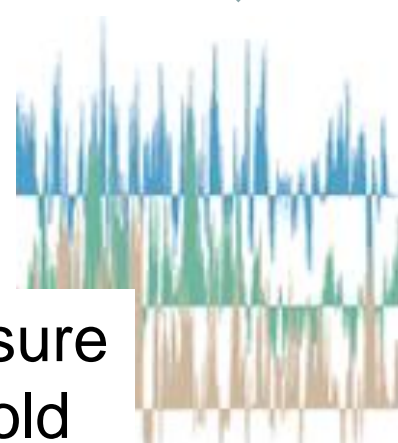


More than 10000 nodes.

Back to the climate system: interpretation (currents, winds, etc.)



Sim. measure + threshold

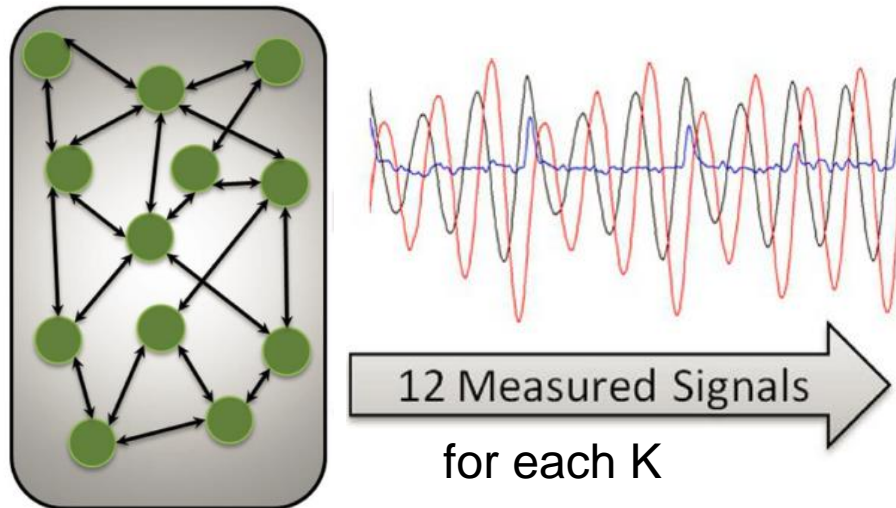


Daily resolution: more than 13000 data points in each TS

Surface Air Temperature Anomalies (solar cycle removed)

# Can we test which Statistical Similarity Measure is optimal for inferring the network connectivity?

- **12** chaotic Rossler oscillators with **known** random connectivity (**19** undirected links).
- The  $x$  variable is recorded for different coupling strengths ( $K$ )



- From the observed signals, different time series can be derived.

$$\{ x_i \} \Rightarrow \{ \varphi_i \} = \text{HT}[x_i] \Rightarrow \{ f_i \} = d\varphi_i/dt$$

Hilbert transform

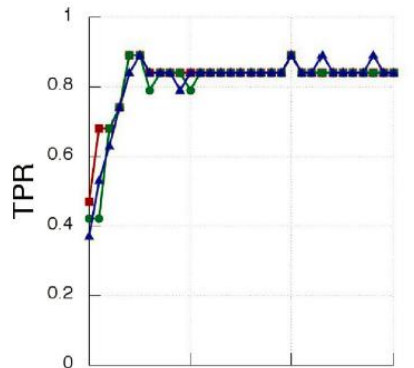
Which one is the “best”?

# How to quantify the success of network inference?

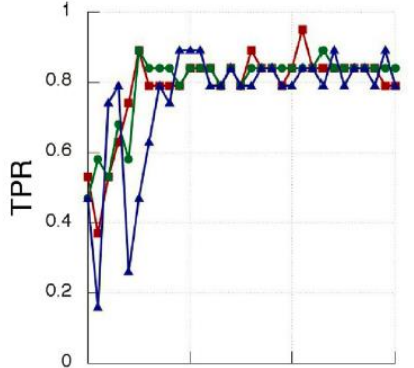
- **True positive rate**: number of correctly detected links / number of existing links;
- **False negative rate**: number of links which are incorrectly classified as not existing / number of existing links;
- **True negative rate**: number of correctly identified non-existing links / number of non-existing links;
- **False positive rate**: number of non-existing links which are incorrectly classified as existing / number of non-existing links.

# Results

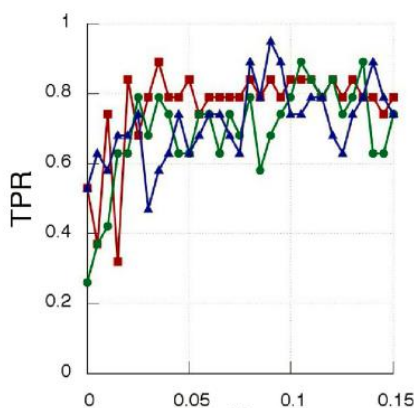
Observed variable (x)



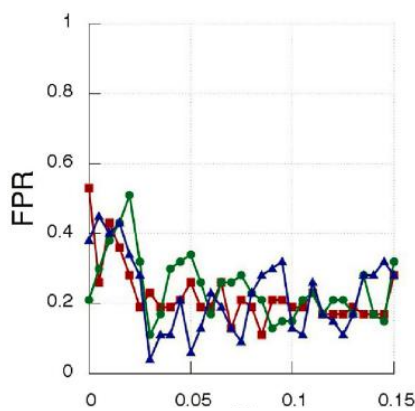
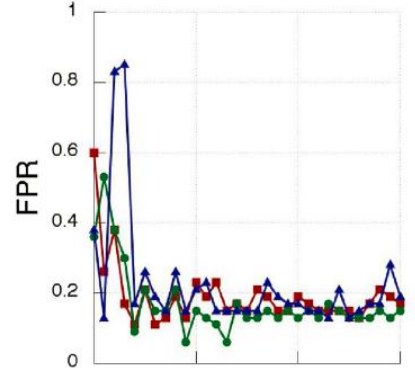
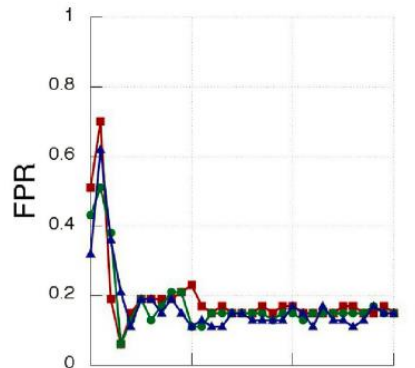
Hilbert phase



Hilbert frequency



Coupling strength, K



Detection threshold **TH** chosen to minimize errors.

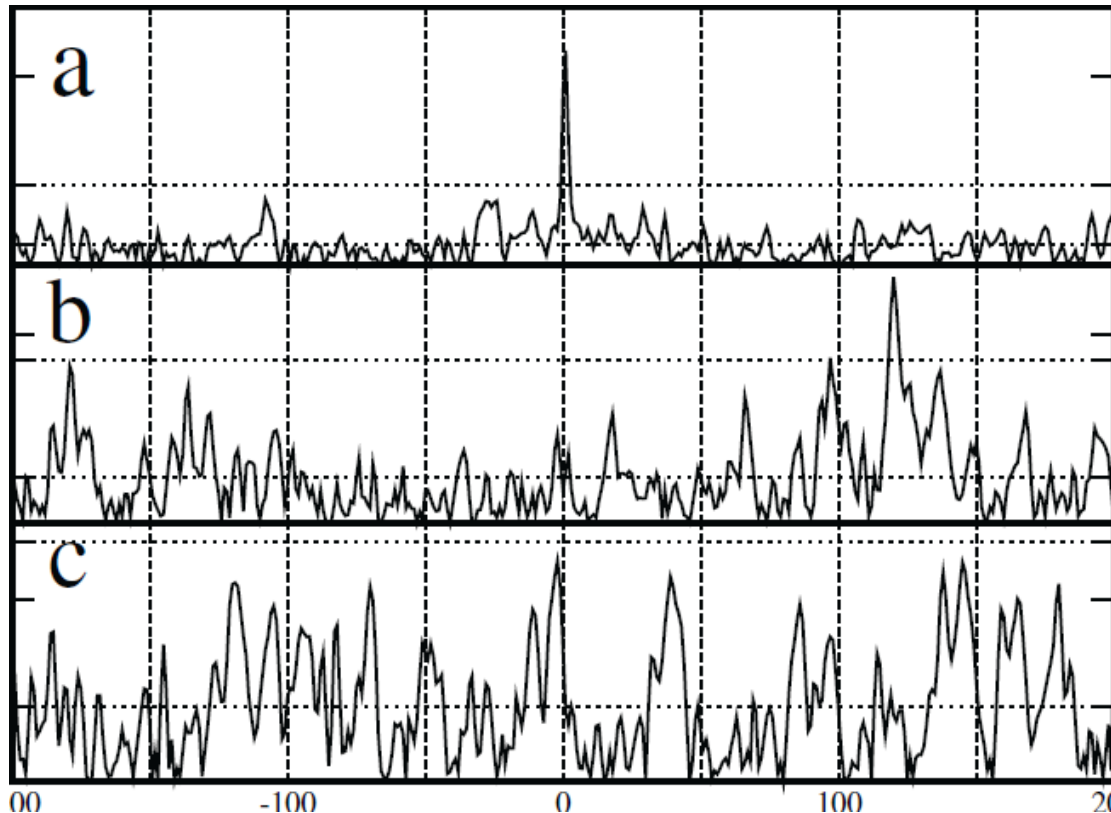
Statistical similarity measures:  
**CC** **MI**  
**MI(symbols)**

- No perfect reconstruction
- No difference between the SSMs & variables

# Can we use the lag information to improve the inference?

$$SSM_{ij} = \max_{\tau_{ij}} SSM_{ij}(\tau_{ij})$$

An example from observed climatic data (temperature anomalies)



A strongly correlated link, with small time delay

An intermediately correlated link, with a few significant time delays.

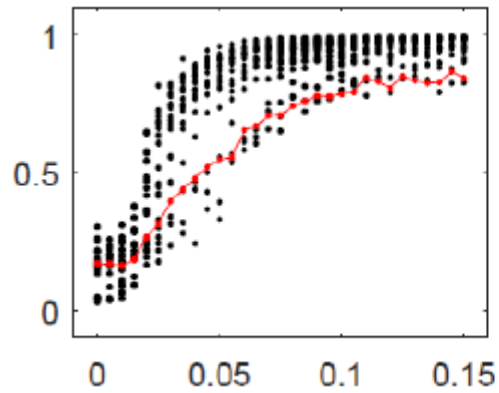
A weakly correlated link, where the local maxima cannot be distinguished from noise.



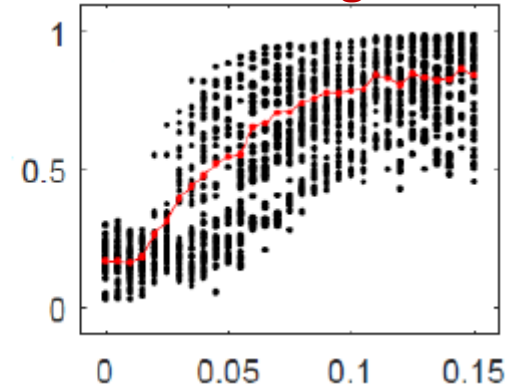
# Lag analysis of the chaotic Rossler oscillators

Statistical  
similarity  
measure  
(CC)

**Existing links**

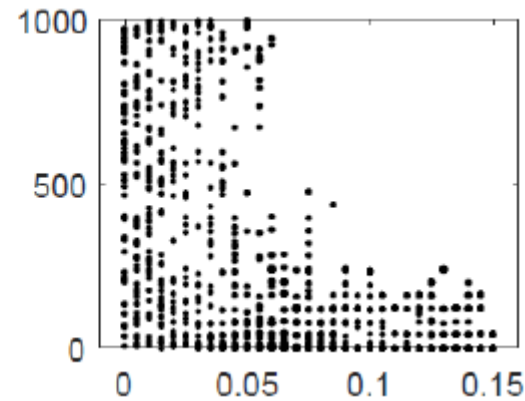
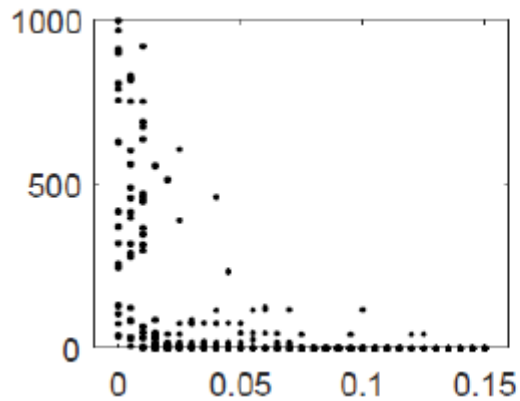


**Non-existing links**



Coupling strength,  $K$

$\tau_{ij}$



Coupling strength,  $K$

## We use two thresholds and compare three criteria to infer the network

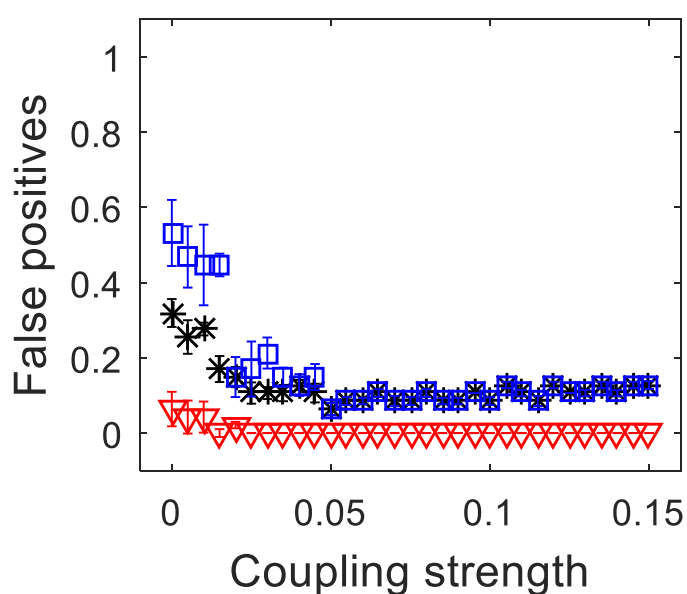
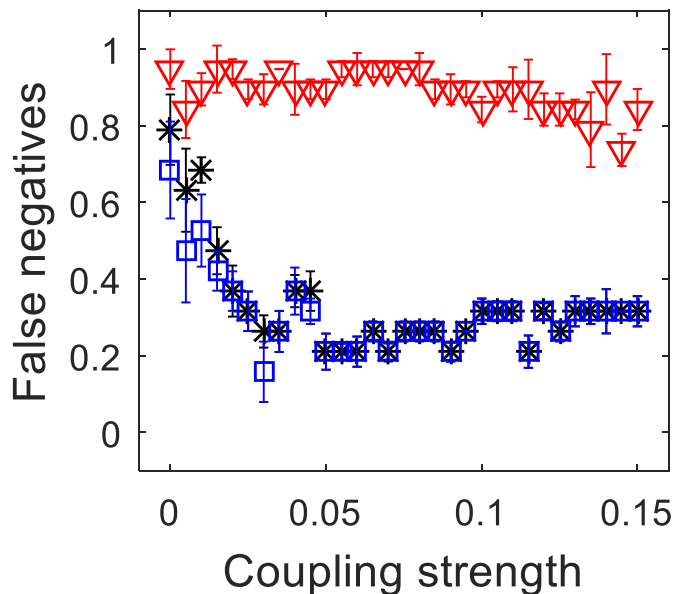
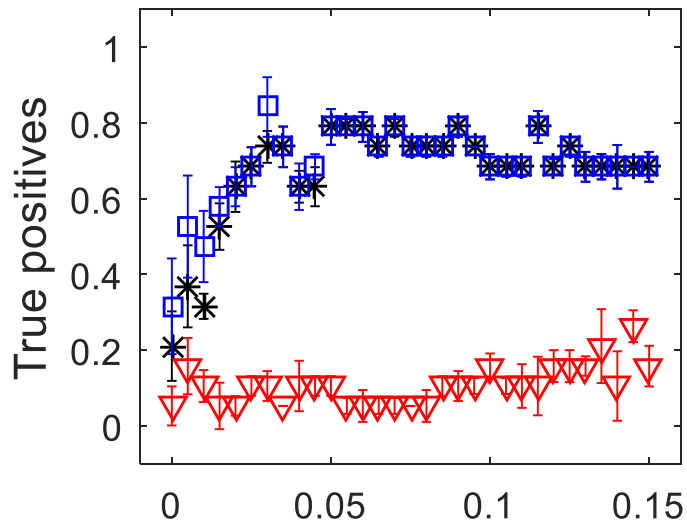
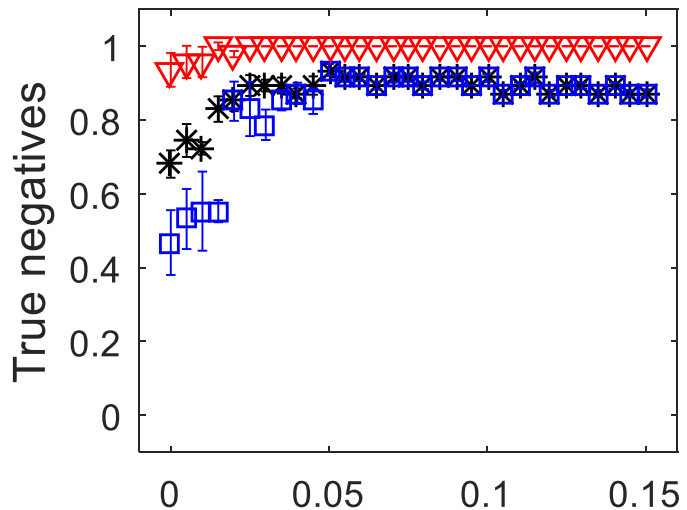
**SIM:** Only the similarity measure (CC) is used to infer the links. The link between  $i$  and  $j$  exists ( $A_{ij}^* = 1$ ) if  $S_{ij} > S_{th}$ , else, the link does not exist ( $A_{ij}^* = 0$ ).

**AND:** The link between  $i$  and  $j$  exists ( $A_{ij}^* = 1$ ) if  $\tau_{ij} < \tau_{th}$  and  $S_{ij} > S_{th}$ , else, the link does not exist ( $A_{ij}^* = 0$ ).

**OR:** The link between  $i$  and  $j$  exists ( $A_{ij}^* = 1$ ) if  $\tau_{ij} < \tau_{th}$  or  $S_{ij} > S_{th}$ , else, the link does not exist ( $A_{ij}^* = 0$ ).

The detection thresholds  $S_{th}$  and  $\tau_{th}$  are chosen to return a given number of links (we assume that we know the number of nodes and the number of links).

# Results



SIM  
AND  
OR

For large coupling SIM & AND give similar results.

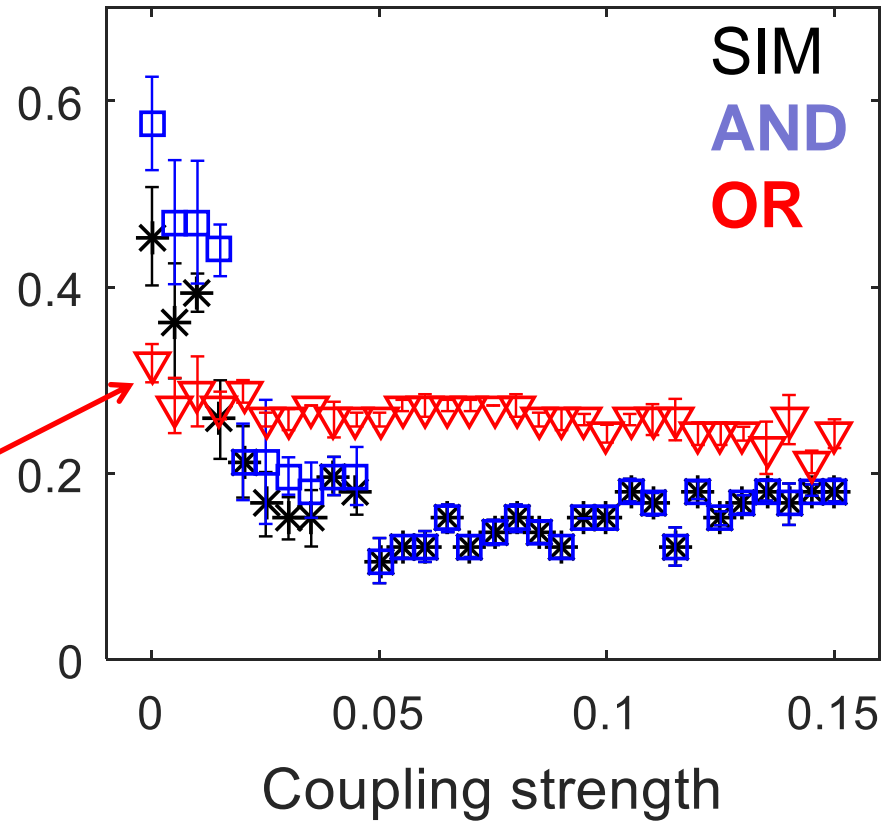
OR minimizes the false positives but fails to detect existing links.

# Total errors (% of wrongly inferred links)

$$\Delta = \frac{FN + FP}{N(N-1)/2}$$

$\Delta$

For weak coupling, the OR criteria reduces the number of errors



# What did we learn?

- For strong coupling, lag information can be used to minimize the false positives but is detrimental to detect existing links.
- For weak coupling, lag information reduces the total number of mistakes.

**Future work:** are these results robust to other types of oscillatory coupled systems?

**Thank you for your attention**

<http://www.fisica.edu.uy/~cris>

G. Tirabassi et al, Sci. Rep. 5 10829 (2015)

N. Rubido and C. Masoller, arXiv:1807.09636 (2018)