Challenges in directed network analysis documented on climate reanalysis surface air temperature data

Monster journey

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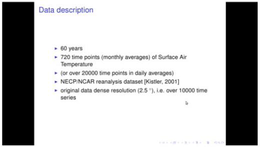
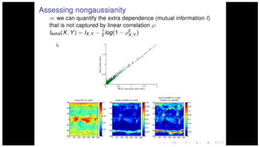
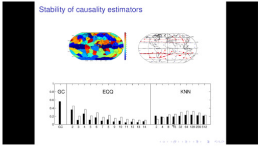
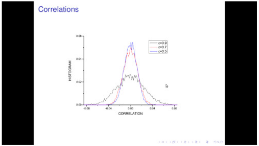
Data

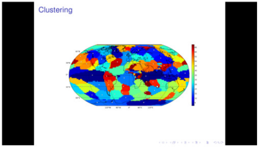
You are
HERE











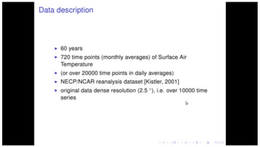
Data description

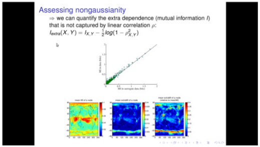
- $\sim$ 9 minutes, 213 time points of whole brain resting state brain activity
- 26 (12 males, 19-54 years) healthy volunteers
- 3T Siemens Magnetom Trio MRI scanner (GE-EPI, TR/TE=2500/30 ms, voxel size=3x3x3mm), a 3D high-resolution T1-weighted image was used for anatomical reference, slice-timing correction, motion correction, spatial normalization to MNI
- original data $\sim$ 20000 time series, dimensionality reduced to 90 time series by averaging over regions from the Automated Anatomical Labeling atlas
- orthogonalized wrt motion parameters, white matter and CSF signal

Data description

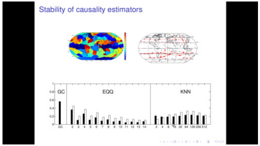
- 60 years
- 720 time points (monthly averages) of Surface Air Temperature
- (or over 20000 time points in daily averages)
- NECP/NCAR reanalysis dataset [Kistler, 2001]
- original data dense resolution (2.5 $^\circ$), i.e. over 10000 time series
- only anomalies with respect to average seasonal changes considered

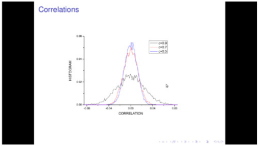
Dependence: how to measure?

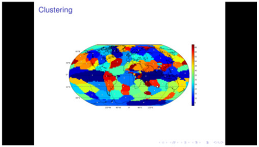




Now you are here!







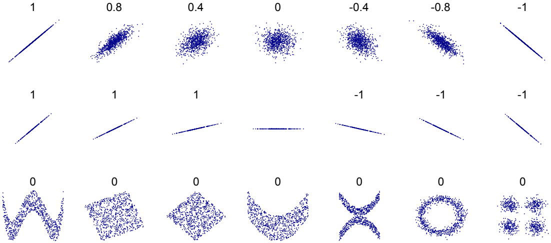
Dependence: how to measure?

Independence ($X \perp\!\!\!\perp Y$): $p(X, Y) = p(X)p(Y)$

Dependence measures:

Pearson's correlation $\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$

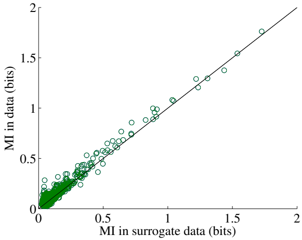
Mutual information: $I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log\left(\frac{p(x,y)}{p(x)\,p(y)}\right)$

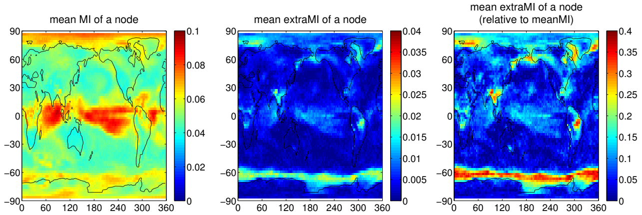


Dependence: Assessing nongaussianity

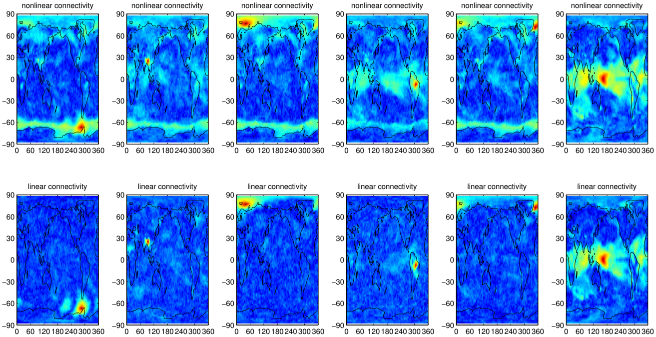
⇒ we can quantify the extra dependence (mutual information I) that is not captured by linear correlation ρ:

$$I_{extra}(X, Y) = I_{X,Y} - \frac{1}{2} log(1 - \rho^2_{X,Y})$$

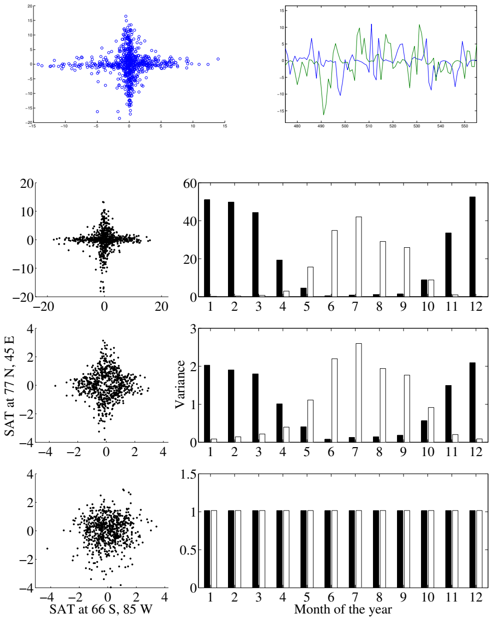




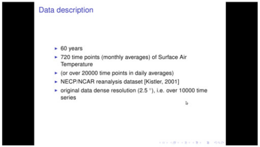
Dependence: nonlinearity examples

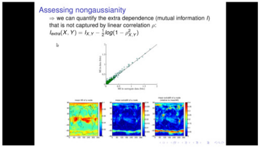


Dependence: Nongaussian ghost of seasonality

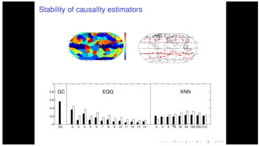


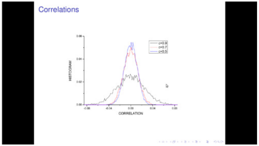
Taking into account autocorrelation

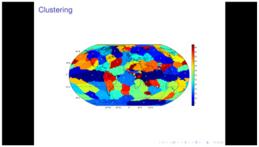




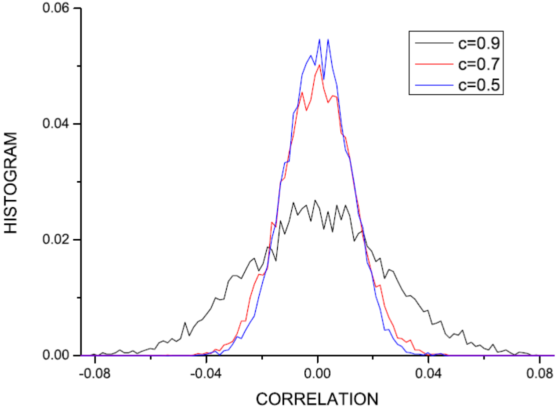
And now here



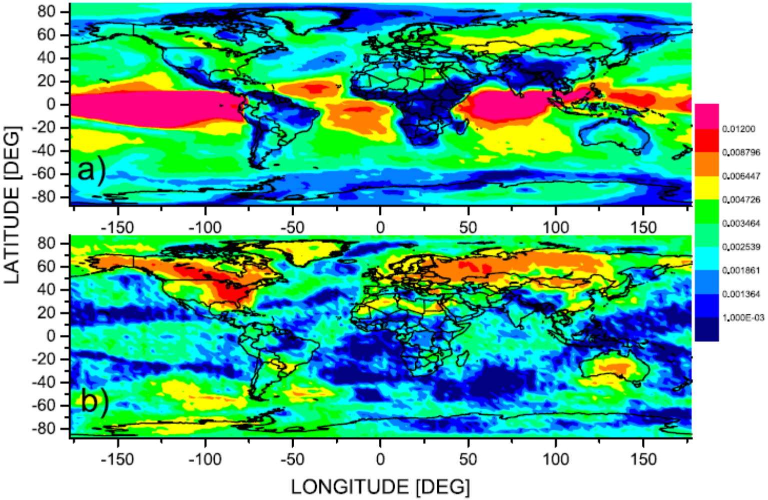




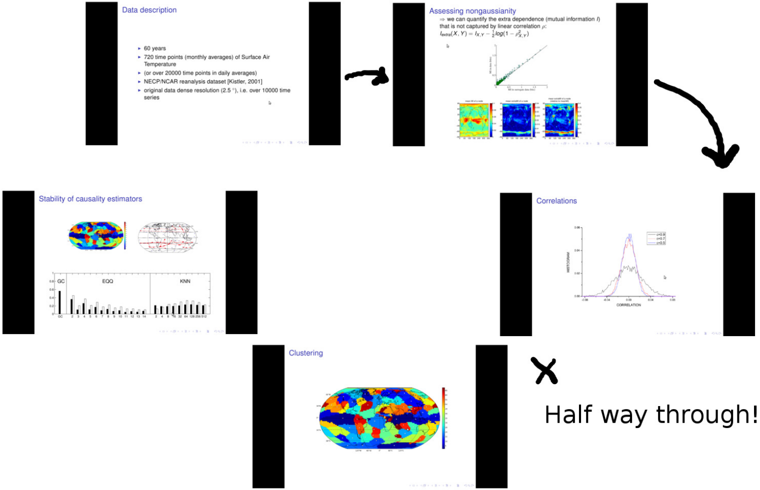
Correlation histogram for (autocorrelated) noise



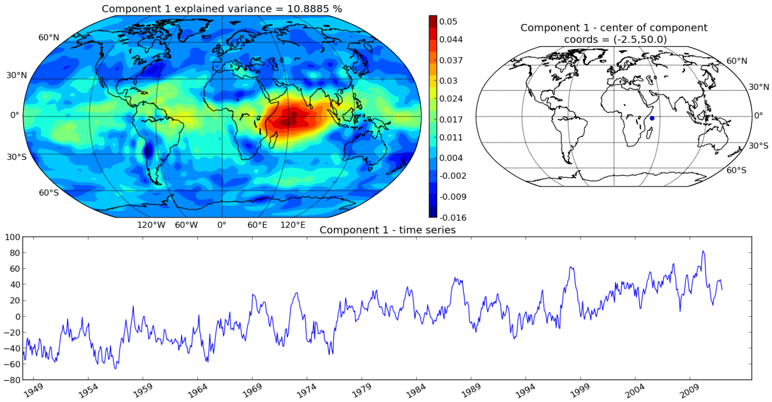
Average weighted correlation with(out) correction



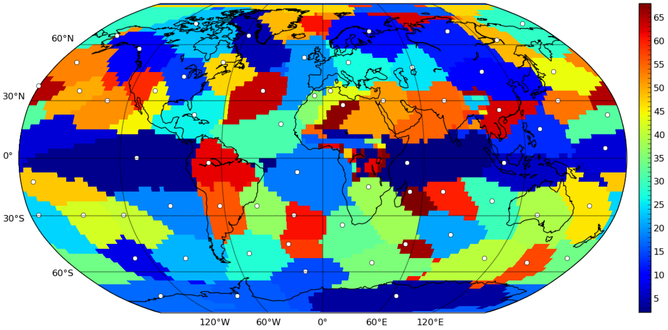
Dimensionality reduction



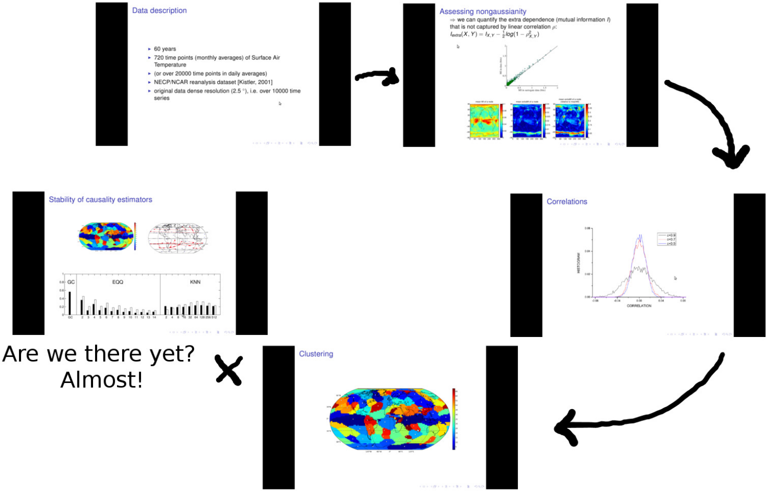
Decomposition



Clustering


60°N
30°N
0°
30°S
60°S
120°W
60°W
0°
60°E
120°E
65
60
55
50
45
40
35
30
25
20
15
10
5

Interaction of subsystems



Causality

- Granger causality: X 'Granger causes' Y iff including the past of Y in a (linear) model of X significantly improves the model fit

$$\mathcal{F}_{Y \to X|Z} = \ln\left(\frac{|\Sigma(\varepsilon_t)|}{|\Sigma(\varepsilon'_t)|}\right)$$

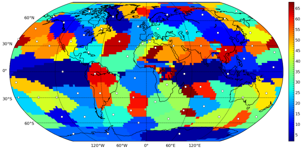
- Transfer entropy: the difference between entropies of the variable X conditioned (or not) on Y:

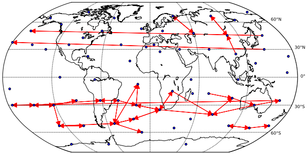
$$\mathcal{T}_{Y \to X|Z} = H(X|X^- \oplus Z^-) - H(X|X^- \oplus Y^- \oplus Z^-),$$

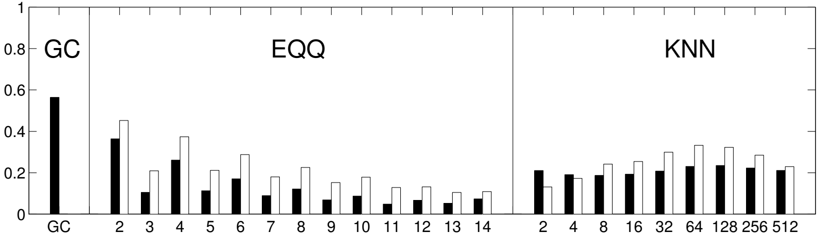
- for stationary linear Gaussian processes GC and TE **equivalent**

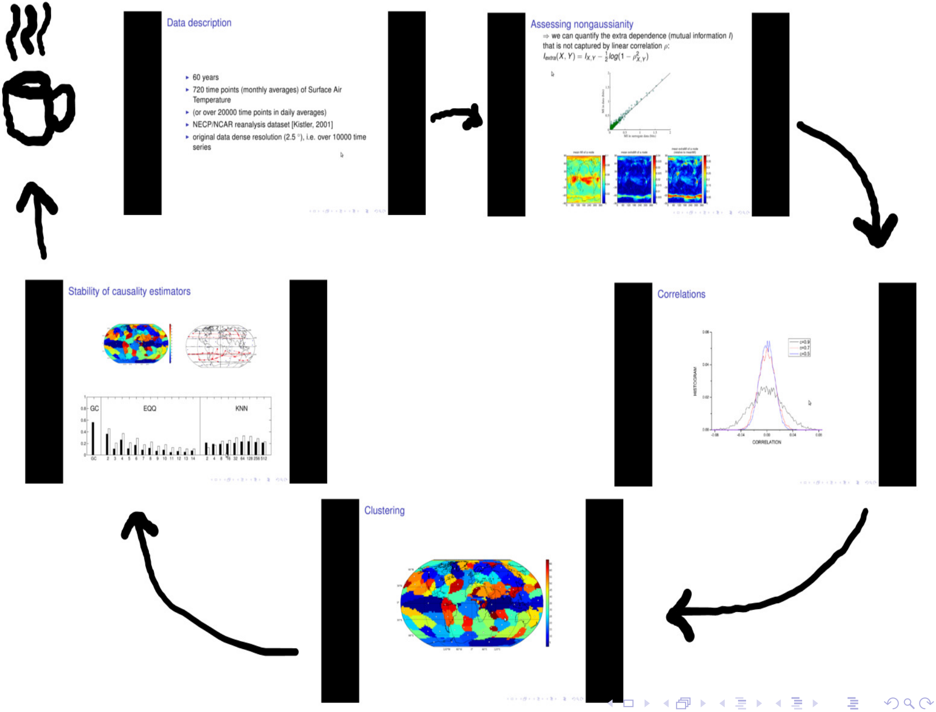
$$\mathcal{F}_{Y \to X|Z} = 2\mathcal{T}_{Y \to X|Z}$$

Stability of causality estimators





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Correlations
HISTOGRAM
CORRELATION
c=0.9
c=0.7
c=0.5
Clustering
Stability of causality estimators
GC
EQQ
KNN

Thank you for your attention!

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References:

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