A causal networks framework for process-oriented dynamical model evaluation

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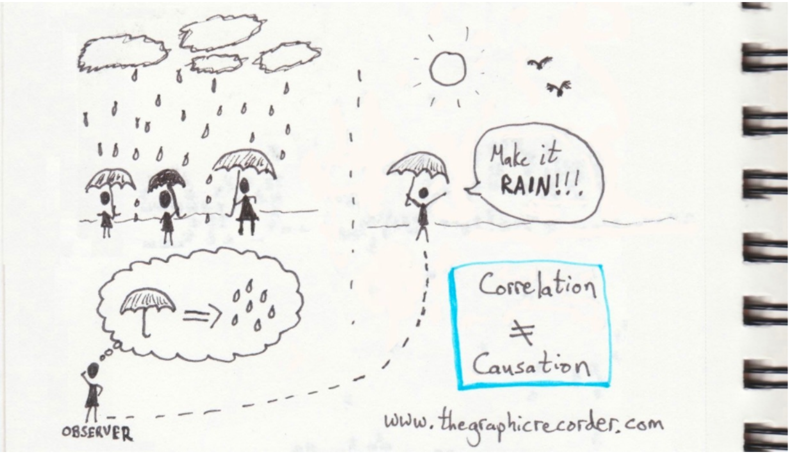
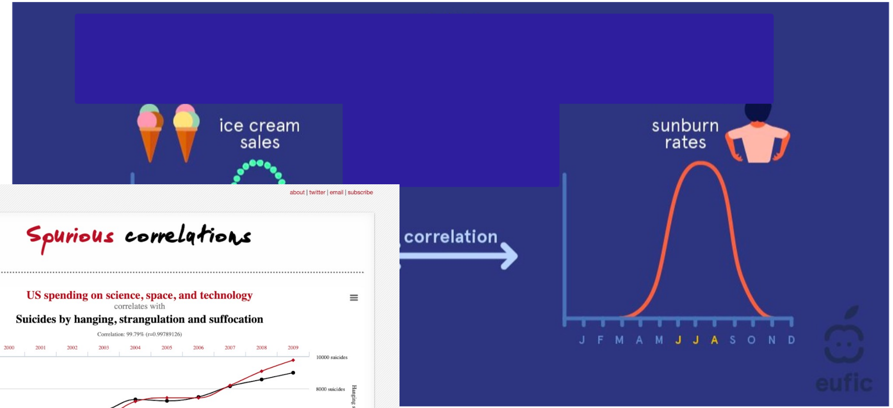
Motivation

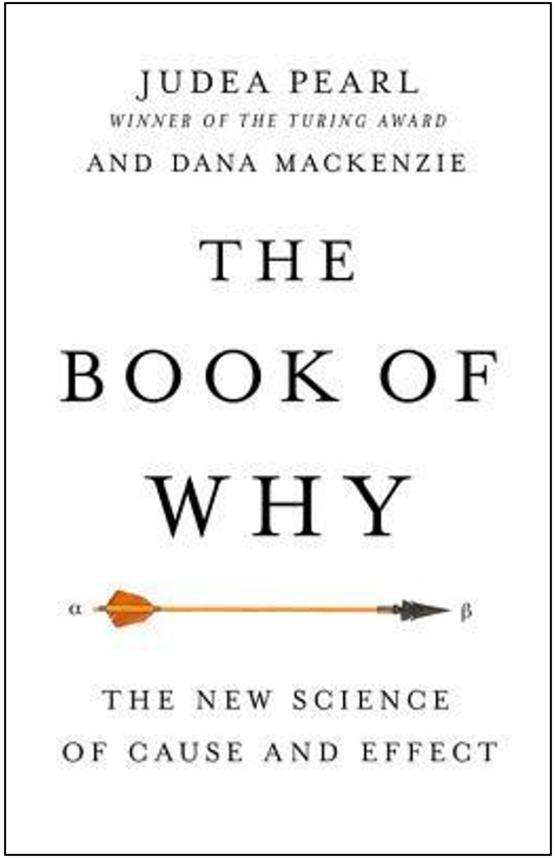
- Correlation coefficient (Pearson or Spearman) is widely used metrics for the Dynamical Model Evaluation.
- For example, teleconnection are classically measured as lagged correlations between climate variables at remote locations.
- However, correlation is incapable to legitimately infer a “cause-and-effect” relationship between two events.
- Causal discovery algorithms go beyond correlation-based measures by systematically excluding common driver effects and indirect links.
- Here, we explore a causal network for model evaluation as a type of process-oriented framework.
- Based on data-driven causal fingerprints, the causal network can understand differences between models and observations based on the physical process which potentially influences model biases in simulating precipitation and temperature.

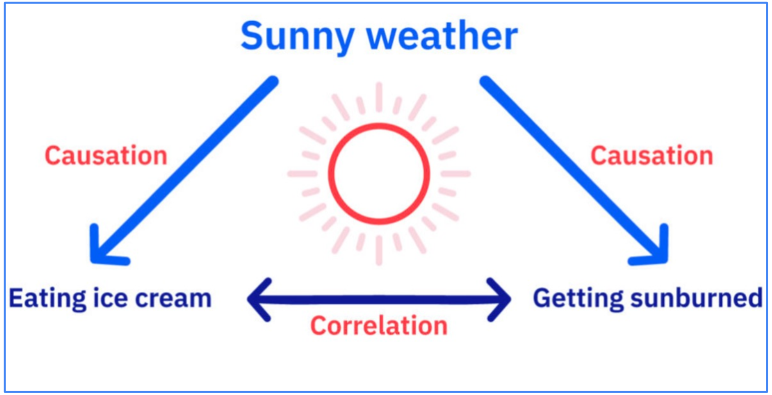
Correlation is not Causation

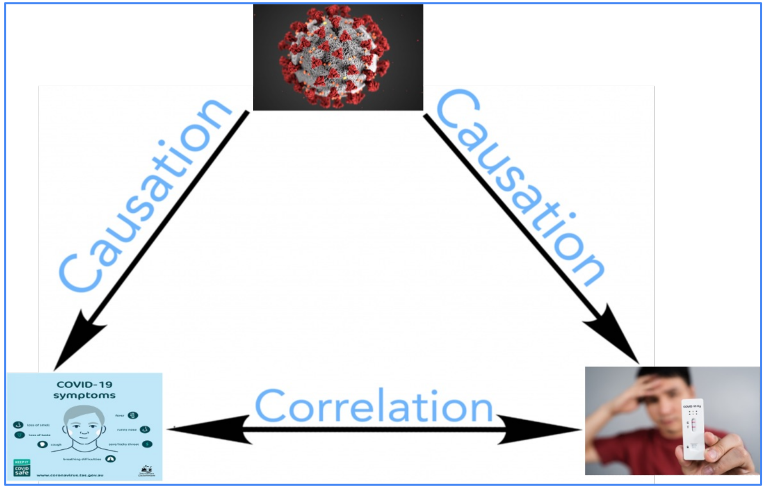




Basics of Causality



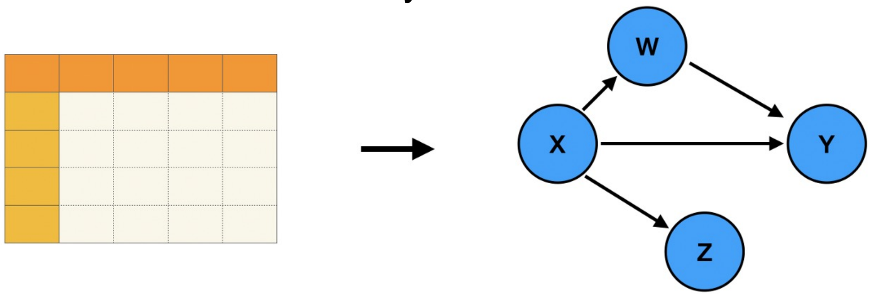




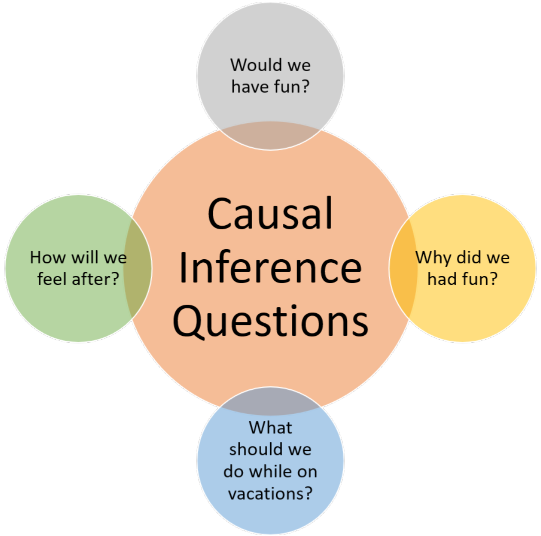
Basics of Causality

- Causal Discovery: Learn the graph/structure from the data
- Causal Inference: Inferring/answering conditional questions from causal graph

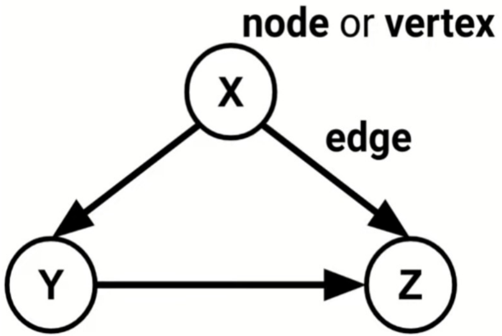
Causal Discovery

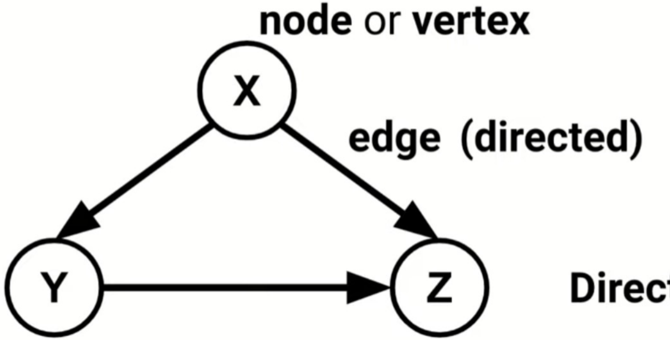


Causal Inference



Basics of Causal Graphs





Directed graph

Adjacent nodes: X and Y, Y and Z

Non-adjacent nodes:
X and Z

X is **parent** of Y

Y is **parent** of Z

Y is **child** of X

Z is **child** of Y

X is **ancestor** of Y and Z

Y is **ancestor** of Z

Y is **descendant** of X

Z is **descendant** of Y and X

Causal Graphs are Directed Acyclic Graphs (DAGs)

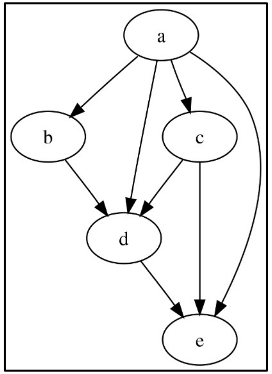
A DAG is a graph that provides a visual representation of causal relationships among a set of variables.

D = directed (all arrows point in only a single direction).The direction of the arrow is the direction of causation: A → B means A causes B.

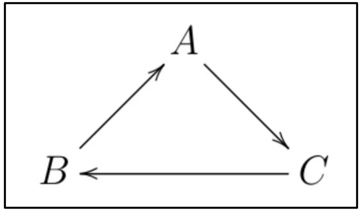
A = acyclic (no sequence of arrows forms a closed loop, which would be backwards causation).Causal Graph should be acyclic.

Several Methods available to find out DAG for Causal Discovery.

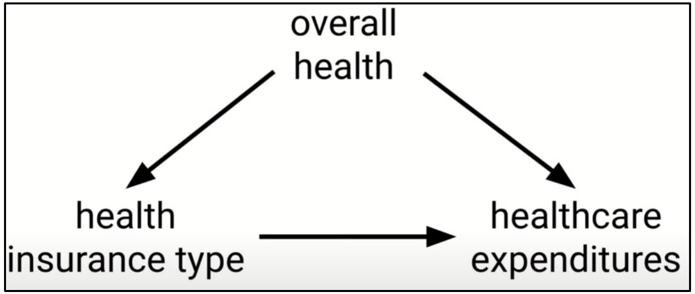
DAG



Not a DAG, Correlation



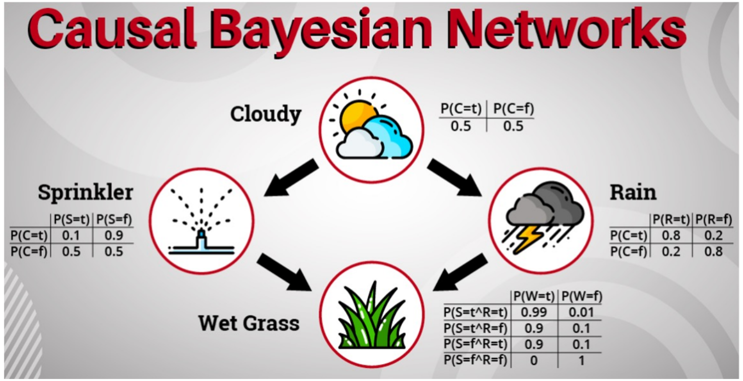
Example



“DAGs with NO TEARS”

- It is a novel method for Bayesian Network (BN) structure learning* based on continuous optimization.
- BN is probabilistic graphical model consists with DAG (each node is random variable) and conditional probability distribution (each edge represents the conditional probability corresponding random variable).
- Estimating the structure of DAGs, is a challenging problem since the search space of DAGs is combinatorial and scales superexponentially with the number of nodes.
- "DAGs with NO TEARS” introduced a fundamentally different strategy: formulate the structure learning problem as a purely continuous optimization problem over real matrices that avoids this combinatorial constraint entirely (Zheng et al.,2018)
- This is achieved by a novel characterization of acyclicity that is not only smooth but also exact.
- Hyperparameter = Threshold ???

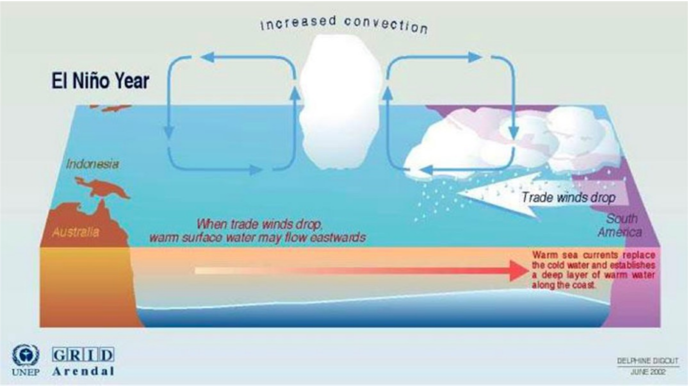
Probabilities of wet grass can be changed based on the information on the cloud, rain, and sprinkler condition

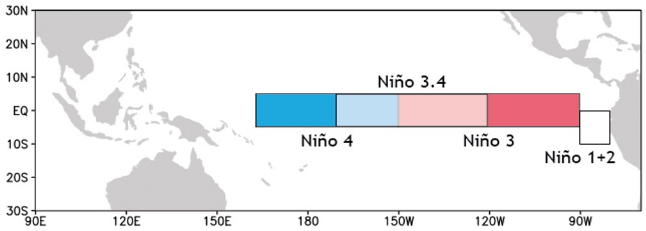


*The structure of a network describing the relationships between variables can be learned from data

Case Study

Inter-relationship between Niño Indices in the real world and seasonal forecast Model. Precursor for El-Nino events.





OPEN

Generation of westerly wind bursts by forcing outside the tropics

Arnold Sullivan[1,2], Wenxiu Zhong[3,4], Gian Luca Eusebi Borzelli[5], Tao Geng[6,7], Chloe Mackallah[1], Benjamin Ng[1], Chi-Cherng Hong[8], Wenju Cai[1,6,7], An-Yi Huang[8] & Roger Bodman[1,9]

The westerly wind burst (WWB) is an important triggering mechanism of El Niño and typically occurs in the western Pacific Ocean. The Fourier spectrum of the wind field over the western tropical Pacific is characterised by a large variety of peaks distributed from intra-seasonal to decadal time scales, suggesting that WWBs could be a result of nonlinear interactions on these time scales. Using a combination of observations and simulations with 15 coupled models from the Coupled Model Intercomparison Project Phase 6 (CMIP6), we demonstrate that the main drivers initiating WWBs are quantifiable physical processes rather than atmospheric stochastic signals. In this study, ensemble empirical mode decomposition (EEMD) from the Holo-Hilbert spectral analysis (HHSA) is used to decompose daily zonal winds over the western equatorial Pacific into seasonal, interannual and decadal components. The seasonal element, with prominent spectral peaks of less than 12 months, is not ENSO related, and we find it to be strongly associated with the East Asian monsoon (EAM) and cross-equatorial flow (CEF) over the Australian monsoon region. The CEF is directly related to the intensity of the Australian subtropical ridge (STR-I). Both the EAM and CEF are essential sources of these high-frequency winds over the western Pacific. In contrast, the interannual wind component is closely related to El Niño occurrences and usually peaks approximately two months prior to a typical El Niño event. Finally, the decadal element merely represents a long-term trend and thus has little to no relation to El Niño. We identified EAM- and CEF-induced westerly wind anomalies in December–January–February (DJF) and September–October–November (SON). However, these anomalies fade in March–April–May (MAM), potentially undermining the usual absence of WWBs in the boreal spring. Similar results are found in CMIP6 historical scenario data.

Westerly wind bursts (WWBs) are a western and central tropical Pacific phenomenon commonly identified a
one of the precursors of El Niño events[1–6]. In 2005, Eisenman et al.[7] suggested that the occurrence and character
istics of WWBs may depend, to some extent, on the state of El Niño-Southern Oscillation (ENSO) components
implying that ENSO itself modulates the WWBs that are associated with the initial onset of ENSO. Westerly win
bursts are often treated as stochastic atmospheric waves that depend the thermocline and produce downwelling
eastward-travelling equatorial Kelvin waves, which create a favourable condition for the development of ENSC
In the available literature, WWBs are defined in several ways. One definition of WWB is a zonal westerly win
anomaly extending at least 10° in longitude, with an average intensity over the western tropical Pacific highe
than 5 m/s and a duration longer than 2 days[2,8–12]. Another commonly adopted definition requires the daily zona
wind anomaly over the western Pacific region (5°S–5°N, 135°E–180°E) to be higher than 0.5 m/s[13]. Previou
studies indicated that WWBs are characterised by strong seasonal, as well as interannual, variations[14–18]. Som
recent studies[19–22], focusing on wind variability in the tropical Pacific over time scales between 20 and 100 days
argued that WWBs may be related to the Madden–Julian oscillation (MJO)[3,8,10,12,23,24]. However, Puy et al.[8] an
Fu & Tziperman[25] found that there is no statistical correlation between the two phenomena. A similar result ca
be found in Hong et al.[21]. MJO and other high-frequency atmospheric signals are mainly related to the Asia

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Datasets used

Observational References:

Niño SST Indices from NOAA’s PSL webpage.

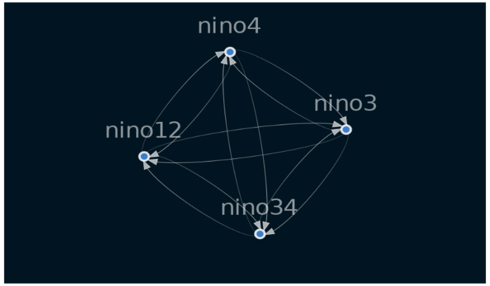
Seasonal Climate Model:

ECMWF-SEAS 5 from Multi-Source Weather (MSWX)-Long (lead -1 hindcast from 1993-2016). Niño SST Indices calculated from SST.

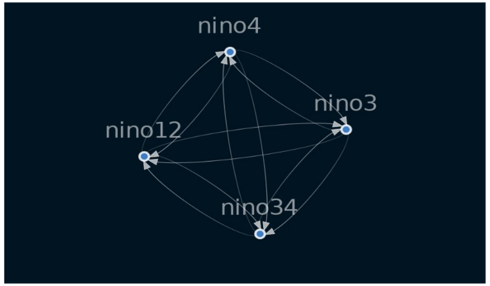
Why Need for causality in this framework?

Correlation between Nino's

Observation

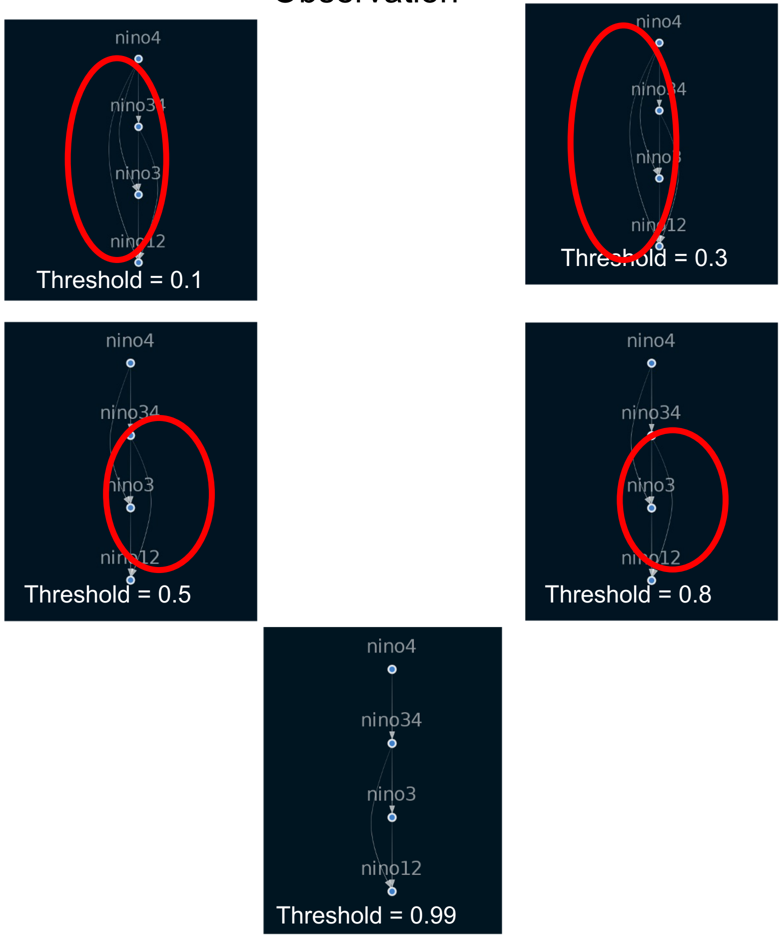


ECMWF-SEAS5

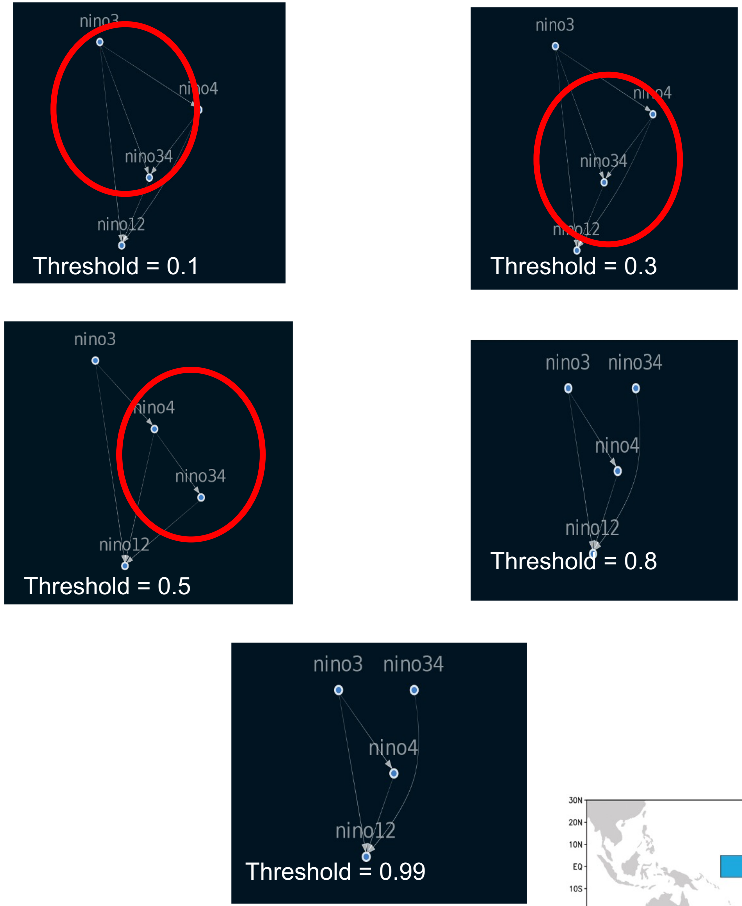


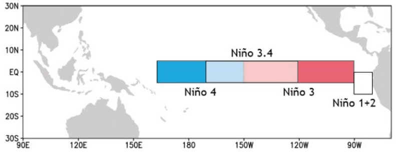
DAG between Nino indices

Observation



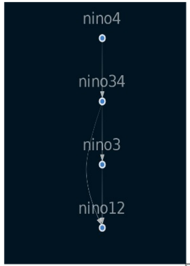
ECMWF-SEAS5





Quantify the Similarity between SEA5 and observational DAG

The Adjacency Matrix

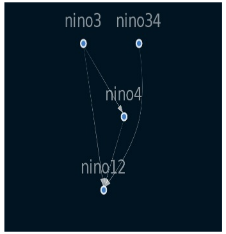


Observation

	Niño 4	Niño 3.4	Niño 3	Niño 1+2
Niño 4	0	1	0	0
Niño 3.4	0	0	1	1
Niño 3	0	0	0	1
Niño 1+2	0	0	0	0

X

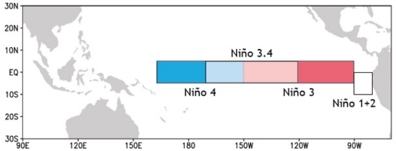
ECMWF-SEAS5



	Niño 4	Niño 3.4	Niño 3	Niño 1+2
Niño 4	0	0	0	1
Niño 3.4	0	0	0	1
Niño 3	1	0	0	1
Niño 1+2	0	0	0	0

= Similarity Score

(Pair-wise Semantic Similarity)



Conclusion

- Correlation need not imply causation
- Causality deals with understanding the cause and effect between different fields
- Causal discovery graphs from observation and dynamical model shows physical pathways of interaction.
- Quantification of similarity between causal discovery graphs of dynamical model and observations provides a causal-metric to assess the fidelity of dynamical models.

Future Work

- Further Development (skill score).
- Compare with other Causal Discovery methods (Granger, PCMCI)
- Multi variate (teleconnection)
- Prediction Causal Inference.

Thank you!

Any Questions/Future collaborations?

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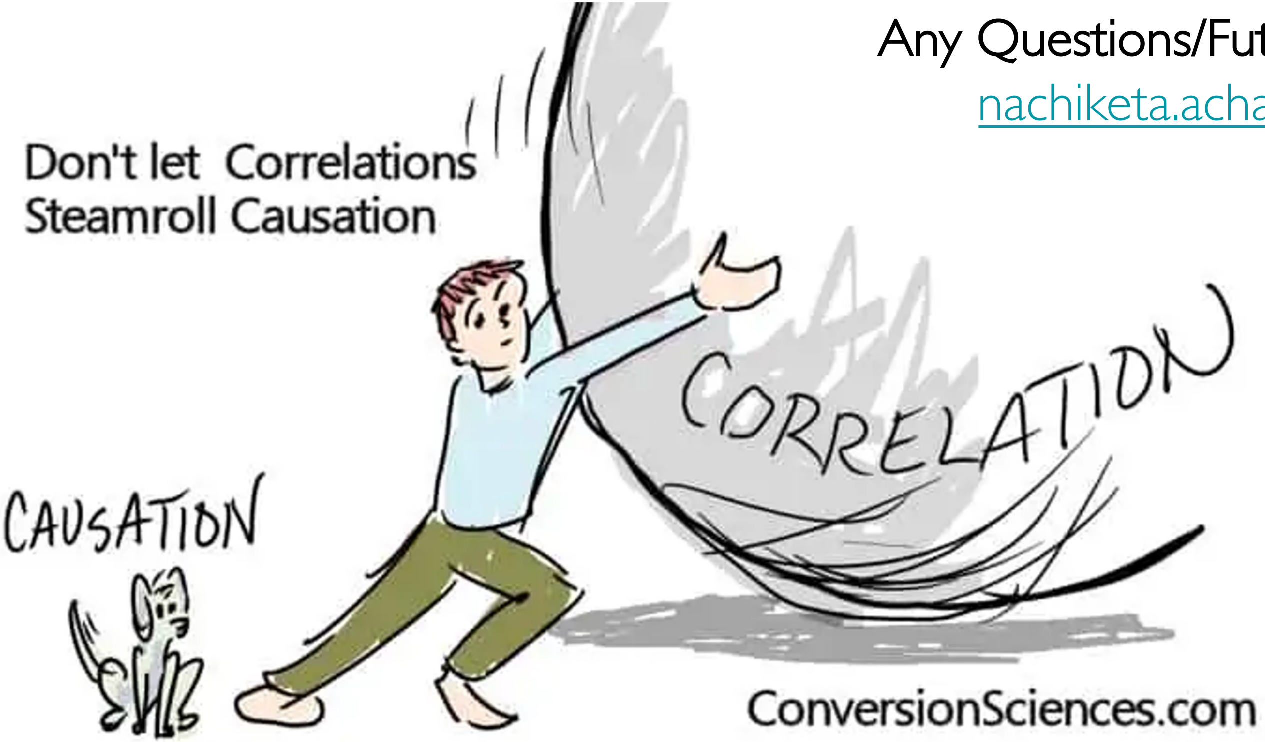
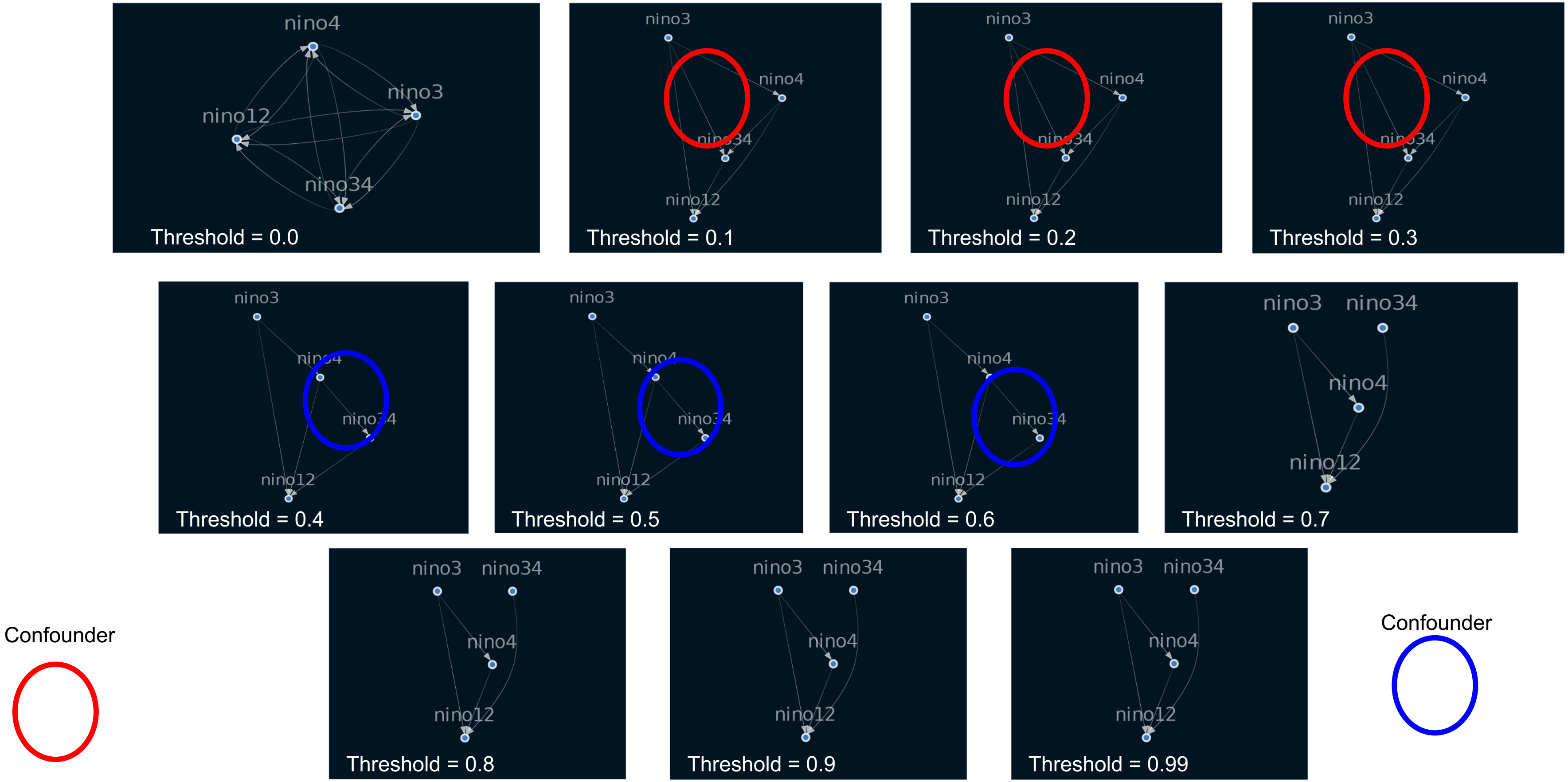
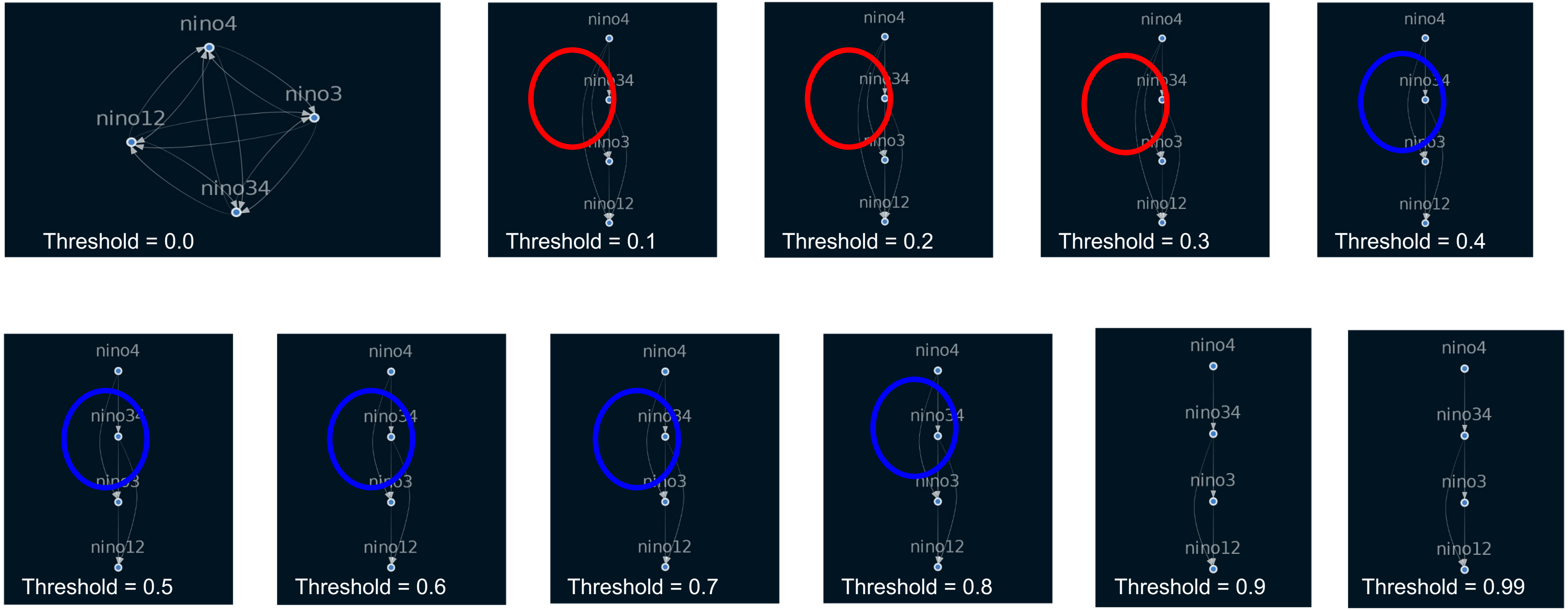


Popular Methods for Discovery

Causal discovery graphs on MSWX 1-month lead data



Causal discovery observational datasets= NOAA PSL



Confounder

Confounder