Detecting Causal Interactions between Atlantic and Pacific Ocean Variability

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Sapienza Università di Roma

Climate Change

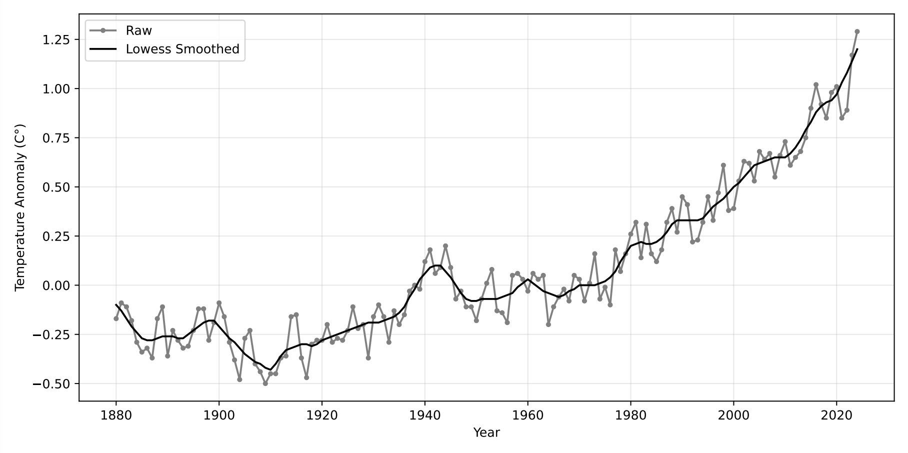
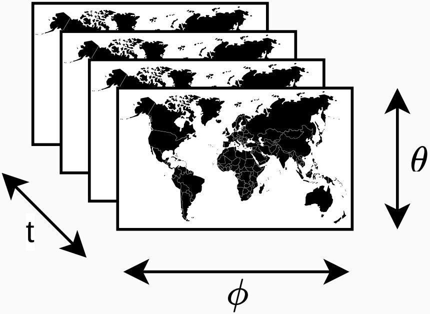


Figure 1: Change in global surface temperature compared to the long-term average from 1951 to 1980 [9].

Data

Sea Surface Temperature (SST)



Name	Resolution t	Resolution ϕ, θ	Time Range	Source
HadISST	Monthly	$\phi = [-180, 180], \theta = [-90, 90]$	1871 – present	[12]
ERSSTV5	Monthly	$\phi = [-180, 180], \theta = [-90, 90]$	1854 – present	[5]

Table 1: Summary of the HadISST and ERSSTV5 datasets.

Climate Indices

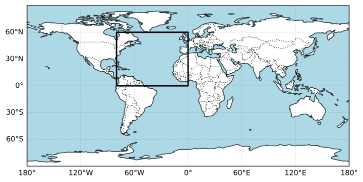


Figure 2: AMV Boundaries

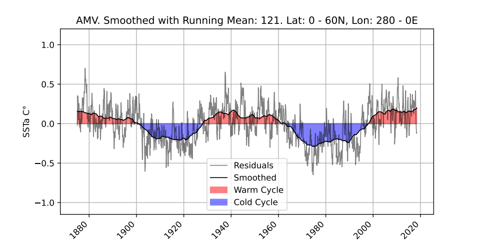
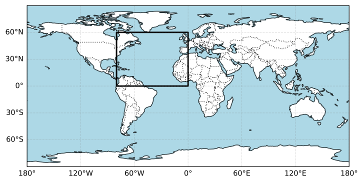


Figure 3: Atlantic Multidecadal Variability (AMV)

Climate Indices



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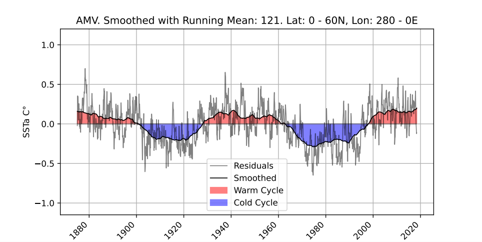

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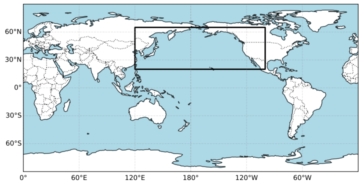


Figure 4: PDO Boundaries

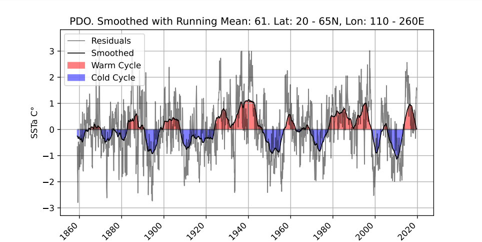


Figure 5: Pacific Decadal Oscillation (PDO)

Research Question

What is the relationship between the AMV and PDO indices?

Pacific Modes of Variability

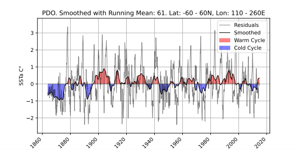


Figure 6: ENSO

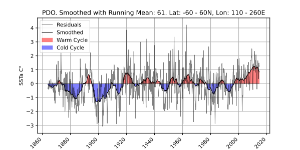


Figure 7: SEPM

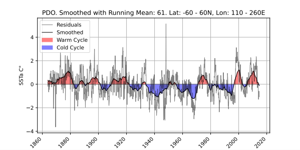


Figure 8: SPDOL

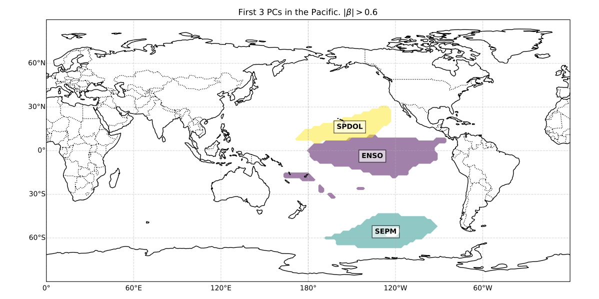
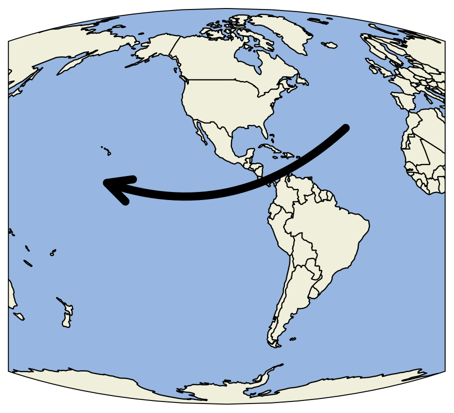


Figure 9: The first 3 varimax rotated principal components in the Pacific 60S to 60N, 110E to 100W.

Existing literature

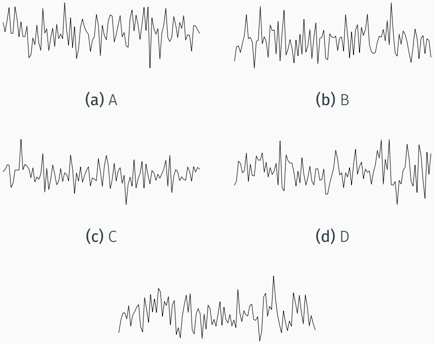
Previous research show a connection from the AMV to the Pacific [16, 10, 2, 15, 1, 3], but use **model simulations**.

We want to use **observational data**.



Causal Discovery Networks

Learn a **causal graph** from **observational** data. In the causal graph, nodes are observations, and edges are causal relationships.



(a) A (b) B (c) C (d) D (e) E

$A = f_A()$ $\quad$ $C = f_C(D)$ $\quad$ $E = f_E(A, C)$

$B = f_B(A, D)$ $\quad$ $D = f_D()$

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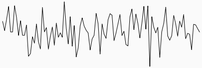
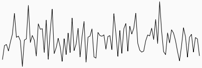


(a) A

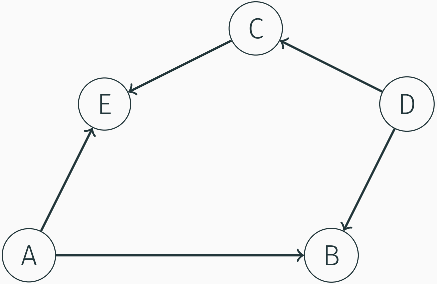


(b) B

(c) C

(d) D

(e) E



$$A = f_A()$$
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$$E = f_E(A, C)$$
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$$D = f_D()$$

Granger Causality

Check if f_{full} has lower prediction error than f_{red}:

$$f_{red} = a_0 + \sum_{i=1}^{p} a_i Y_{t-i} + \epsilon_t, f_{full} = b_0 + \sum_{i=1}^{p} b_i Y_{t-i} + \sum_{j=1}^{q} c_j X_{t-j} + \eta_t \quad (1)$$

PCMCI+

Use conditional independence (CI) tests to iteratively remove links from a complete graph.

$$X \perp\!\!\!\perp Y \quad | \quad Z \quad (2)$$

LKIF

Use a maximum likelihood estimator (MLE) to estimate the rate of entropy transfer between variables in the system. A link exists if the information transfer is statistically significant at level α.

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Methods

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Experiment Setup

Apply Granger Causality, PCMCI+, LKIF to two networks, at $\alpha = 0.05$, $\tau = 12$:

Network 1

- AMV
- PDO

Network 2

- AMV
- PDO
- PC1 Varimax Rotated (ENSO)
- PC2 Varimax Rotated (SEPM)
- PC3 Varimax Rotated (SPDOL)

Result Graphs

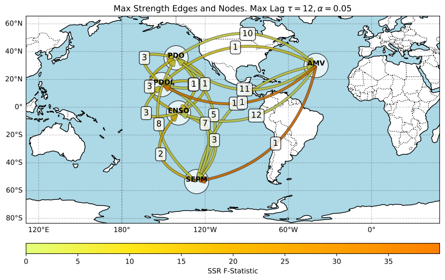


Figure 11: Granger Causality

Result Graphs

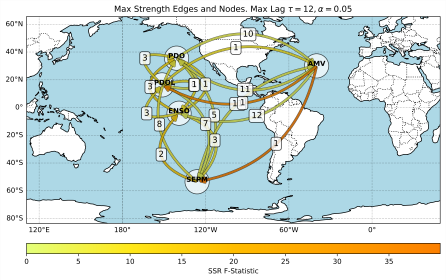


Figure 11: Granger Causality

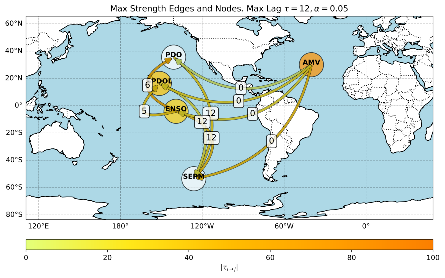
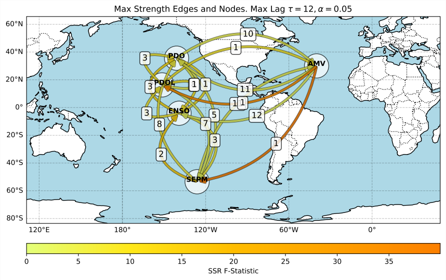


Figure 12: LKIF

Result Graphs



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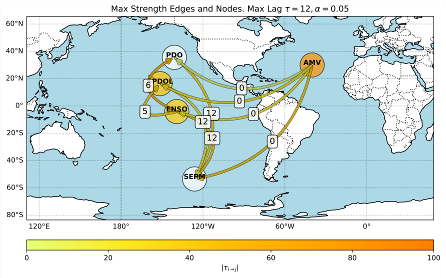

Figure 12: LKIF

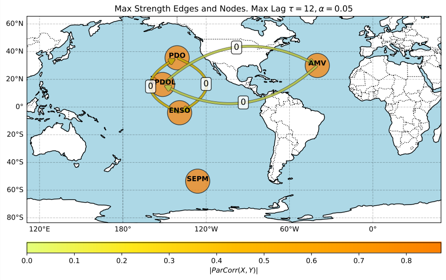

Figure 13: PCMCI+

Result Edge Strengths - from AMV

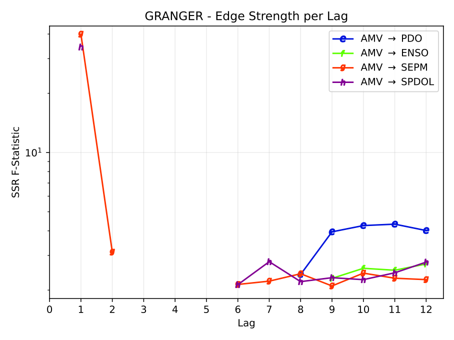

Figure 14: Granger Causality

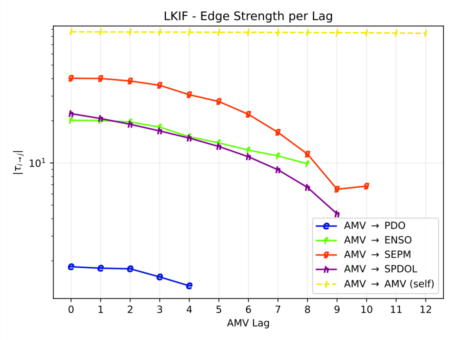

Figure 15: LKIF

Result Edge Strengths - to PDO

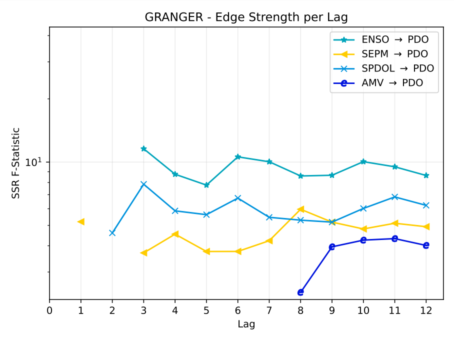

Figure 16: Granger Causality

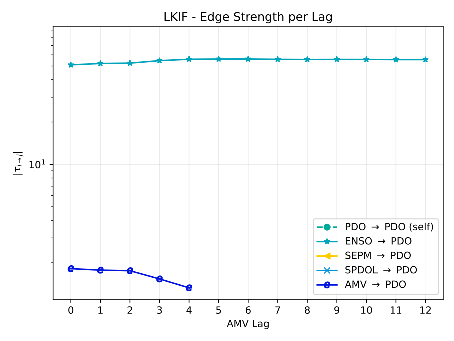

Figure 17: LKIF

Conclusion

- Granger Causality and LKIF find links from AMV to PDO $\rightarrow$ changes in the Atlantic are followed by changes in the Pacific.
- Links from AMV to PDO tend to be weaker than links from other Pacific modes to PDO (Figure 16, Figure 17) $\rightarrow$ PDO is be modulated by AMV via other Pacific components.

Conclusion

- Granger Causality and LKIF find links from AMV to PDO $\rightarrow$ changes in the Atlantic are followed by changes in the Pacific.
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References

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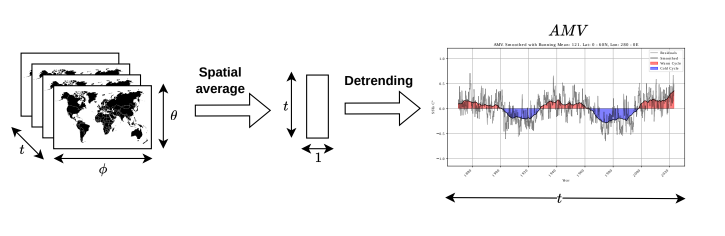
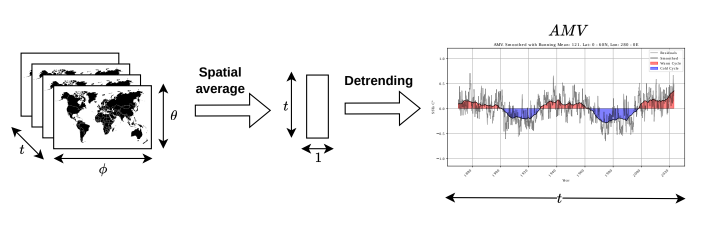


Figure 18: Atlantic Multidecadal Variability (AMV)

Climate Indices



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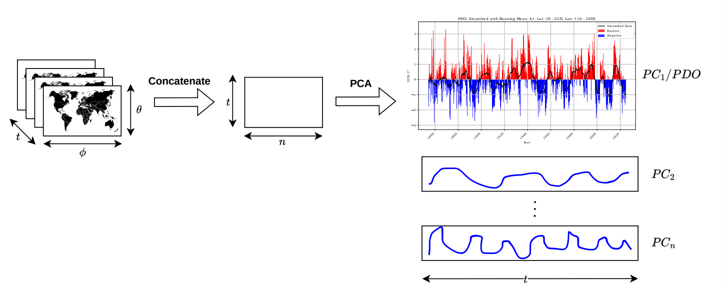
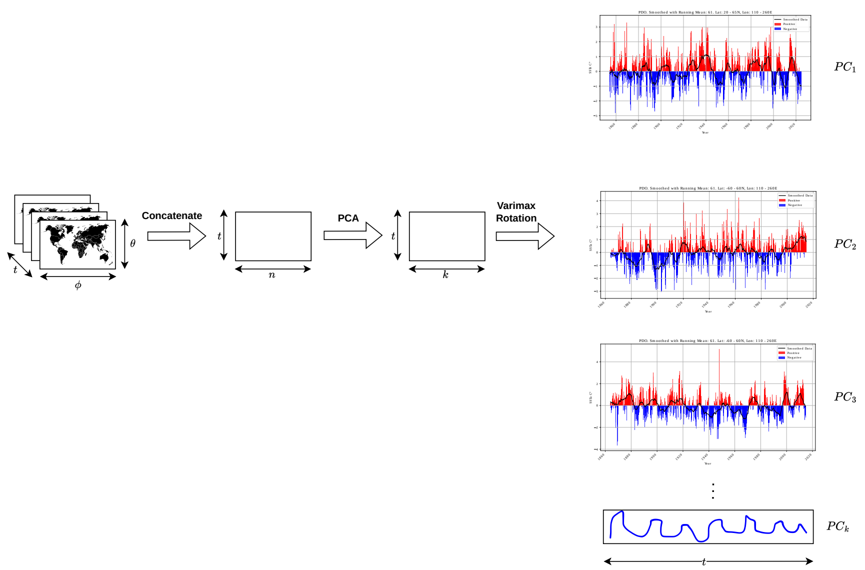


Figure 19: Pacific Decadal Oscillation (PDO)

Varimax Rotation

Enrich the system by adding more Pacific variables, computed via PCA followed by a Varimax rotation.



Granger Causality [4, 11]

Given timeseries X (cause) and Y (effect), fit **two** regression models to predict Y:

$$f_{red} = a_0 + \sum_{i=1}^{p} a_i Y_{t-i} + \epsilon_t \tag{3}$$

$$f_{full} = b_0 + \sum_{i=1}^{p} b_i Y_{t-i} + \sum_{j=1}^{q} c_j X_{t-j} + \eta_t \tag{4}$$

Compare using F-test where F is:

$$F = \frac{SSE_{red} - SSE_{full}/(r-s)}{SSE_{full}/(T-r)} \tag{5}$$

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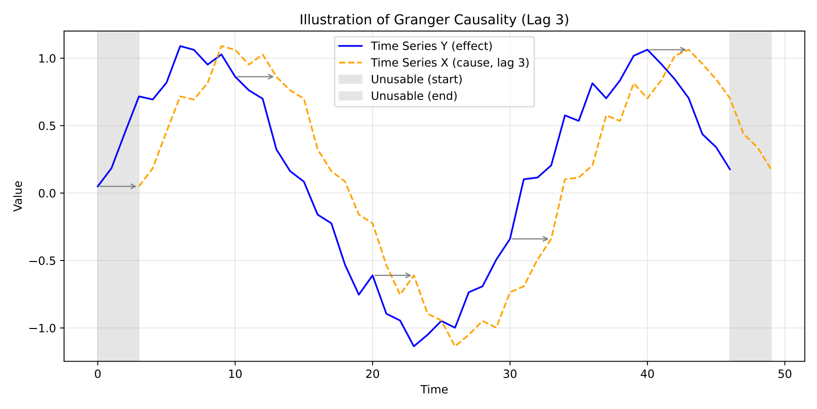

Figure 21

PCMCI+ [14, 13]

Use **Conditional Independence** (CI) tests to determine if two variables are independent **given** a set Z.

$$X_i \perp\!\!\!\perp X_j | Z \tag{6}$$

1. Start with fully connected graph.
2. Discover lagged parents $\widehat{B_t^-}(X_t^i)$.
3. Condition on lagged parents $\widehat{B_t^-}(X_t^i)$ and contemporaneous connections S to refine parent set.

$$MCI : X_i^{t-\tau} \perp\!\!\!\perp X_j^t \quad | \quad S, \widehat{B}_-^t(X_j^t) \setminus \left\{X_i^{t-\tau}\right\}, \widehat{B}_-^{t-\tau}(X_i^{t-\tau}) \tag{7}$$

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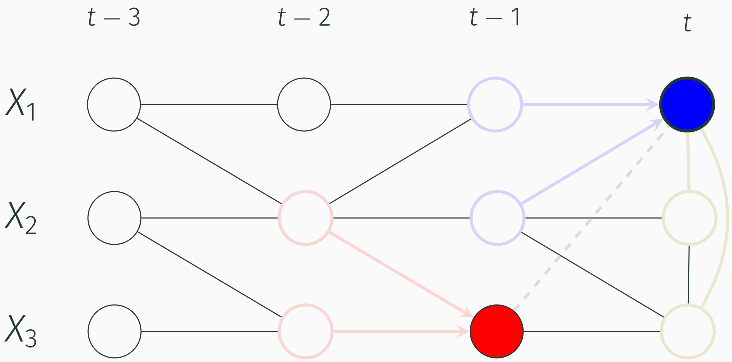
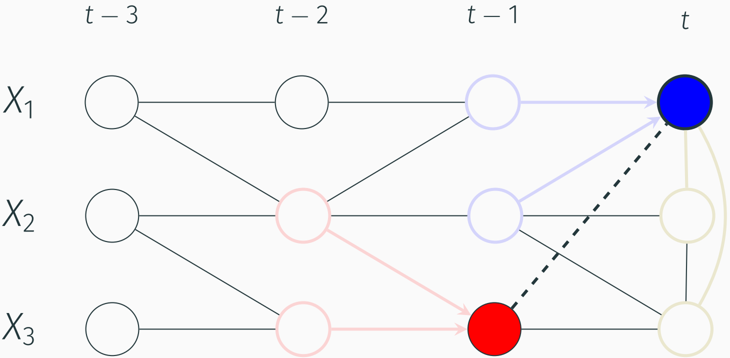
PCMCI+ Timeseries Graph



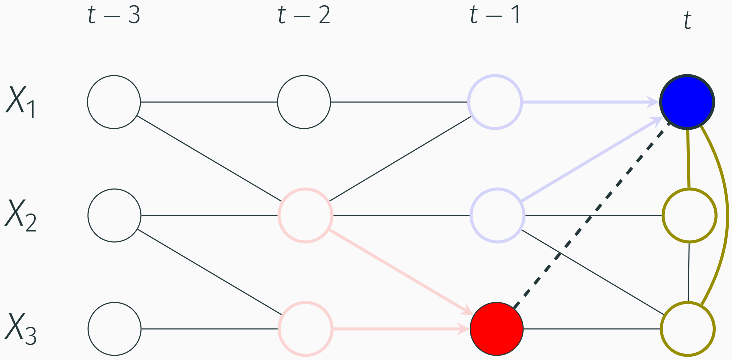
$$MCI : \mathbf{X_3^{t-1}} \perp\!\!\!\perp \mathbf{X_1^t} \quad | \quad S, \widehat{\mathcal{B}}^{t-1}_{-}(X_3^{t-1}), \widehat{\mathcal{B}}^{t}_{-}(X_1^t) \setminus \{X_3^{t-1}\} \tag{8}$$

PCMCI+ Timeseries Graph



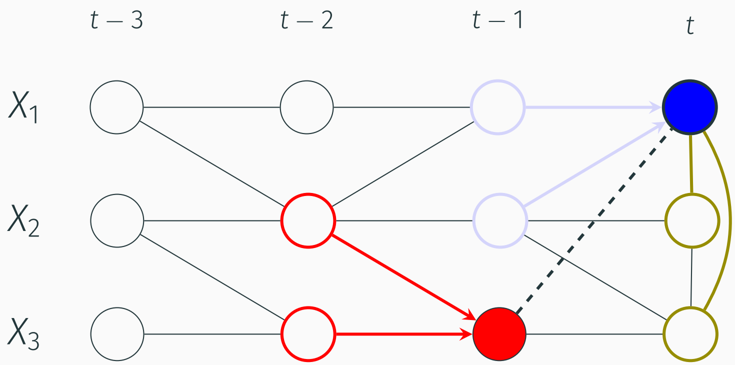
$$MCI : \mathbf{X_3^{t-1}} \perp\!\!\!\perp \mathbf{X_1^{t}} \quad | \quad S, \widehat{B}_-^{t-1}(X_3^{t-1}), \widehat{B}_-^{t}(X_1^{t}) \setminus \{X_3^{t-1}\} \tag{8}$$

PCMCI+ Timeseries Graph



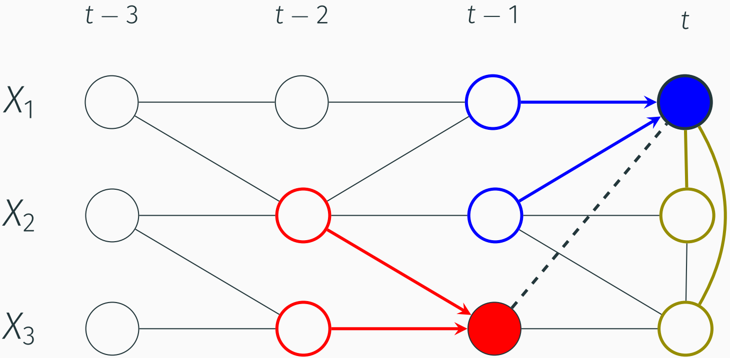
$$MCI : \mathbf{X_3^{t-1}} \perp\!\!\!\perp \mathbf{X_1^t} \quad | \quad S, \widehat{B}_-^{t-1}(X_3^{t-1}), \widehat{B}_-^t(X_1^t) \setminus \{X_3^{t-1}\} \tag{8}$$

PCMCI+ Timeseries Graph



$$MCI : \mathbf{X_3^{t-1}} \perp\!\!\!\perp \mathbf{X_1^t} \quad | \quad S, \widehat{\mathcal{B}}_-^{t-1}(X_3^{t-1}), \widehat{\mathcal{B}}_-^{t}(X_1^{t}) \setminus \{X_3^{t-1}\} \tag{8}$$

PCMCI+ Timeseries Graph



$$MCI : \mathbf{X_3^{t-1}} \perp\!\!\!\perp \mathbf{X_1^{t}} \quad | \quad S, \widehat{B}^{t-1}_{-}(X_3^{t-1}), \widehat{B}^{t}_{-}(X_1^{t}) \setminus \{X_3^{t-1}\} \tag{8}$$

LKIF [8, 7, 6]

Measure the **information flow** between variables, using a Maximum Likelihood Estimator (MLE).

$$\hat{T}_{i \to j} = \frac{1}{det\mathbf{C}} \sum_{k=1}^{d} \Delta_{jk} C_{k,di} \frac{C_{ij}}{C_{ii}} \tag{9}$$

Normalised with

$$Z_i = \sum_{k=1}^{d} \left| \hat{T}_{k \to i} \right| + \left| \frac{dH_i^{noise}}{dt} \right| \tag{10}$$