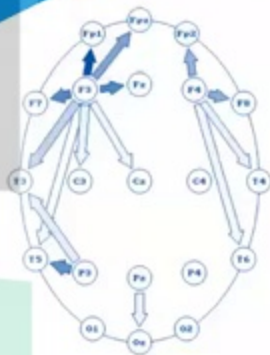




# Finding Causal Relationships

*Granger Causality vs. Transfer Entropy*

Rami Khushaba, *PhD*



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March  
2022



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# Granger Causality

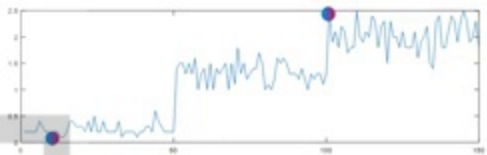
The equation for the Auto-regressive model of order  $p$  (**RESTRICTED MODEL, RM**)

$$X_t = \alpha + \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \dots + \gamma_p X_{t-p}$$

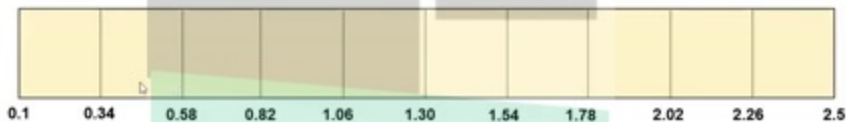
where  $p$  parameters (degrees of freedom) to be estimated.

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# Histogram Approach



1. Find the **minimum (min)** and **maximum (max)** & **range (max-min)**
2. Select the number of histogram bins yourself, say for example 10 bins.
3. Divide the range by the number of selected bins, that is  $(\text{max}-\text{min})/10$



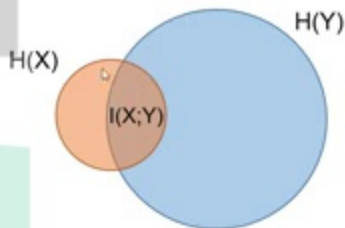
# Normalized Mutual Information

- Normalized variants can be developed by dividing the mutual information by the entropy of the corresponding variables.

$$C_{XY} = \frac{I(X;Y)}{H(Y)} \quad \text{and} \quad C_{YX} = \frac{I(X;Y)}{H(X)}.$$

The two coefficients have a value ranging in  $[0, 1]$ , but are not necessarily equal. In some cases, a symmetric measure may be desired, such as the following redundancy measure

$$R = \frac{I(X;Y)}{H(X) + H(Y)}$$



# Granger Causality vs. Transfer Entropy

The success of the GC and TE approaches strongly depends on the characteristics of the system under study (its dimensionality, the strength of the coupling, the length and the temporal resolution of the data, the level of noise contamination, etc.).

Both approaches can fail in distinguishing genuine causal interactions from correlations that arise due to similar governing equations, or correlations that are induced by the presence of common external forcings.

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