

Controlling the false positive rate of Granger causality tests in fMRI data

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Centre for Complex Systems and Brain and Mind Centre collaboration
USYD



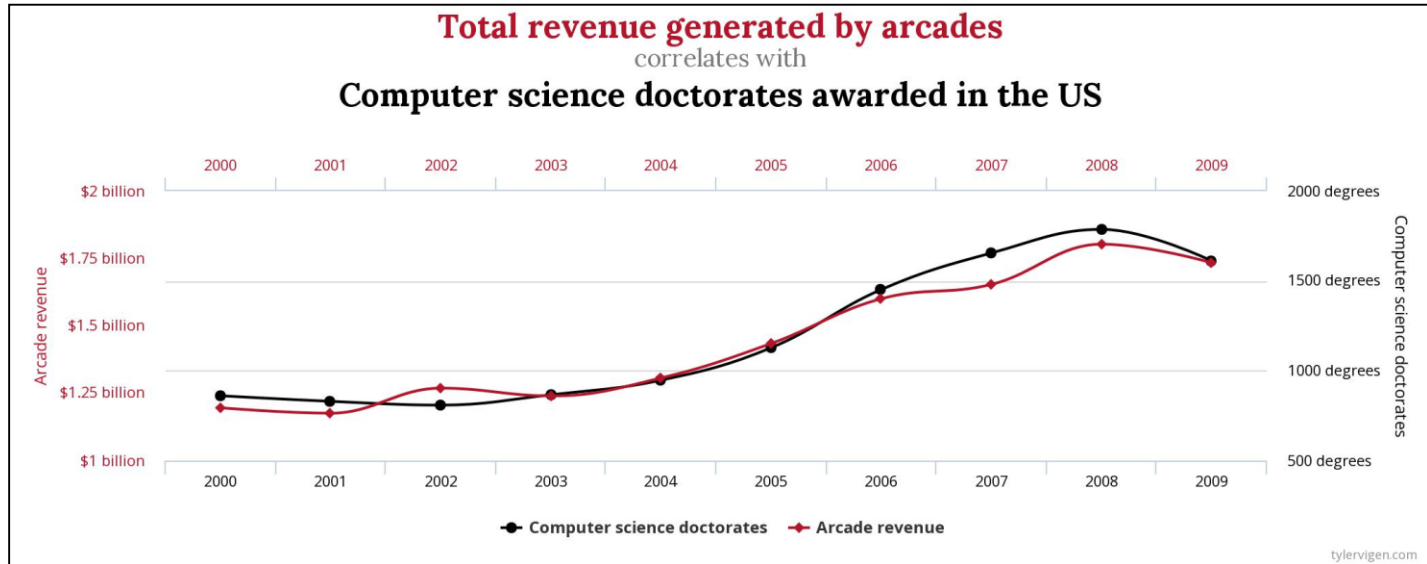
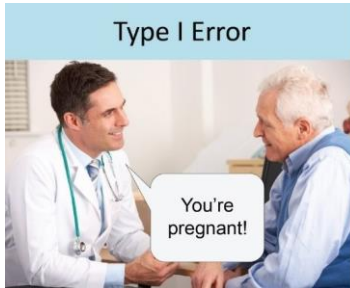


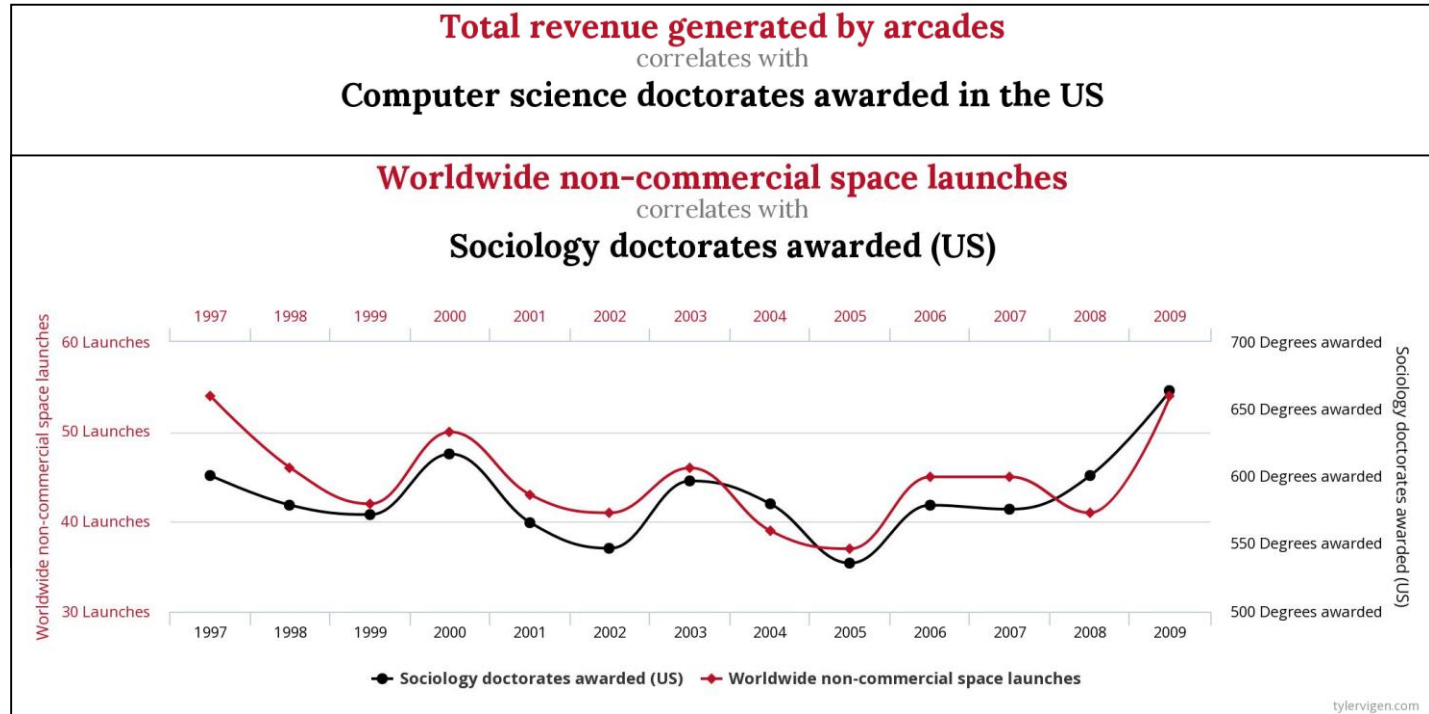
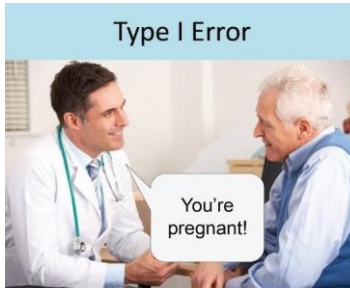
Type I Error

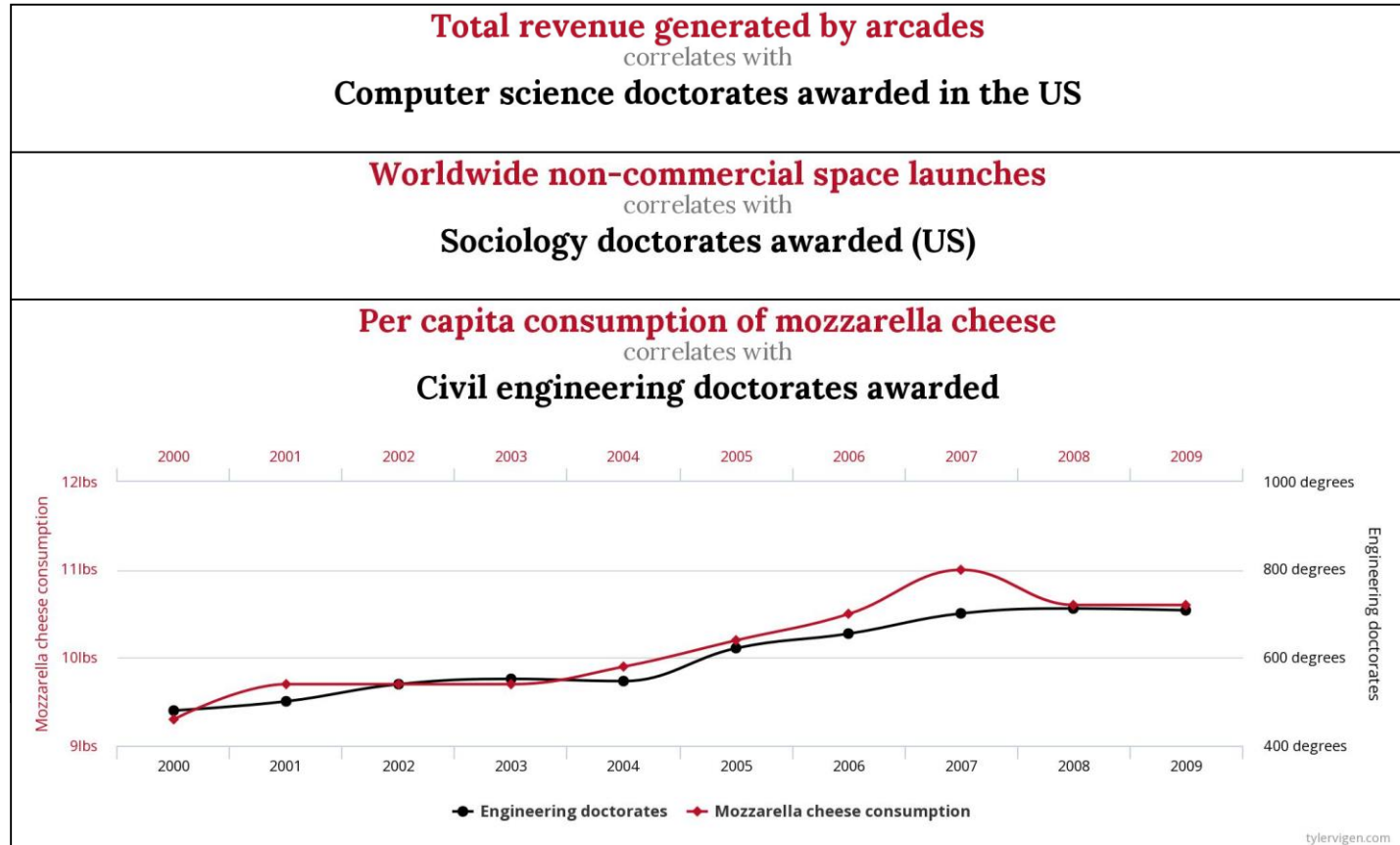
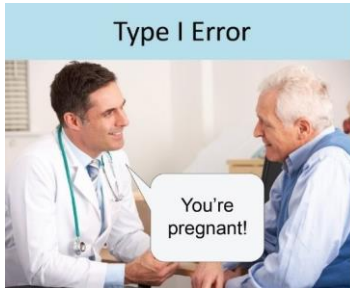


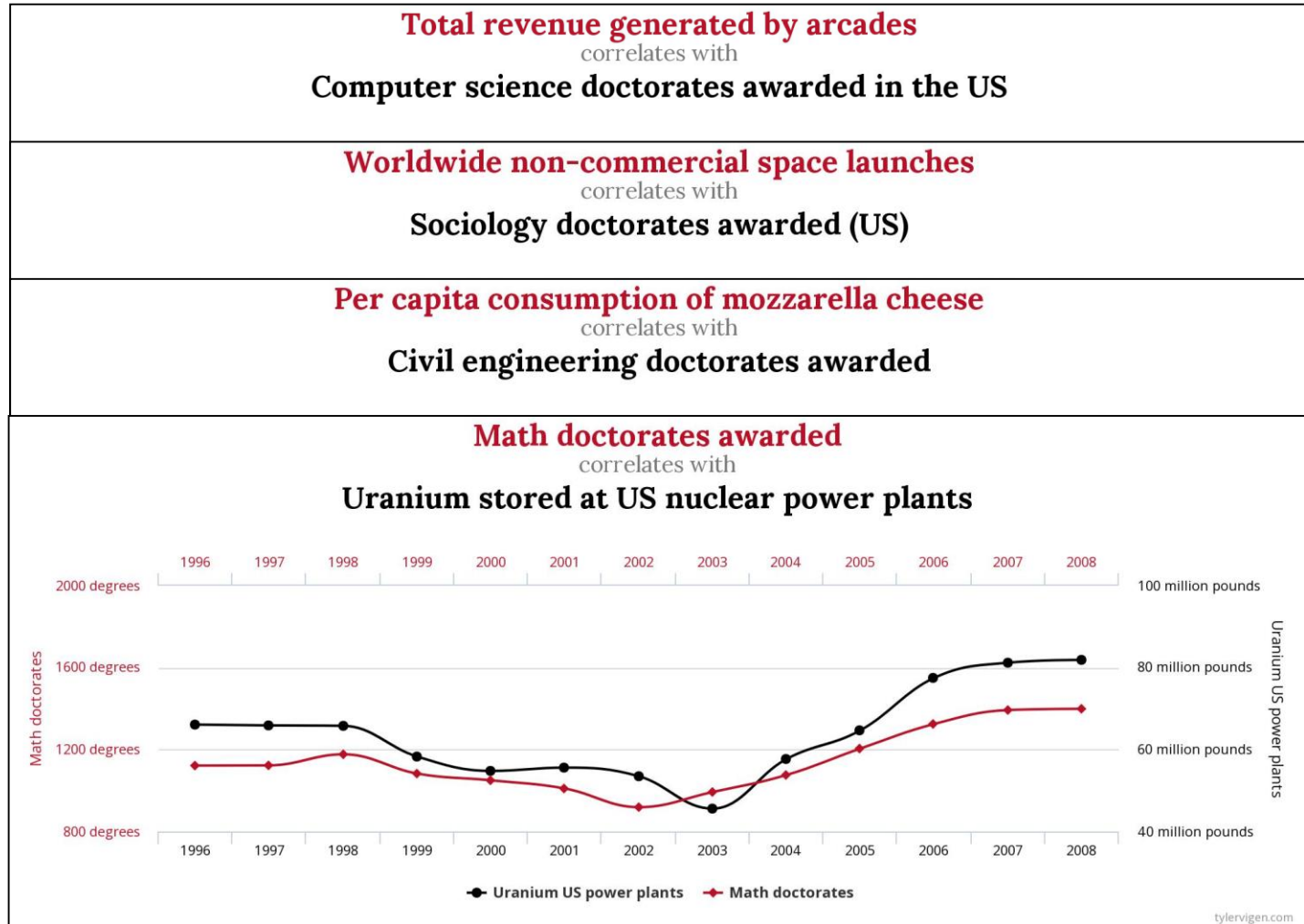
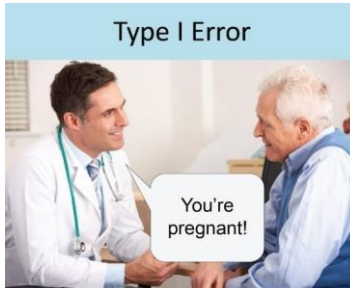
Type II Error











- › These problems also occur in neuroscience
 - Naturally autocorrelated processes, e.g., fMRI and M/EEG
 - Autocorrelation through filtering (common to isolate 0.01 to 0.1 Hz for fMRI)
- › A number of common dependence measures are overestimated:
 - Correlation
 - Granger causality
 - Mutual information
 - Conditional mutual information
- › We propose methods for controlling this FPR

Increased false positive rates

Ridiculous question: Does one patient's fMRI data influence another's?

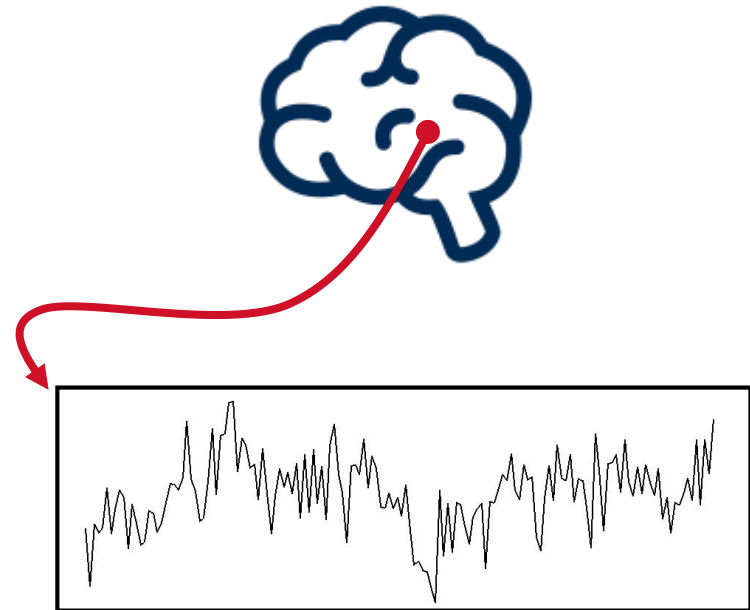
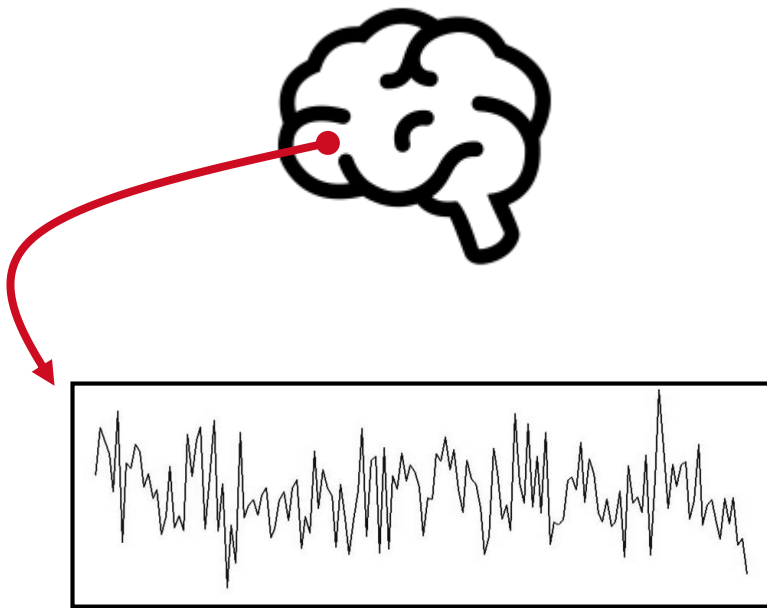
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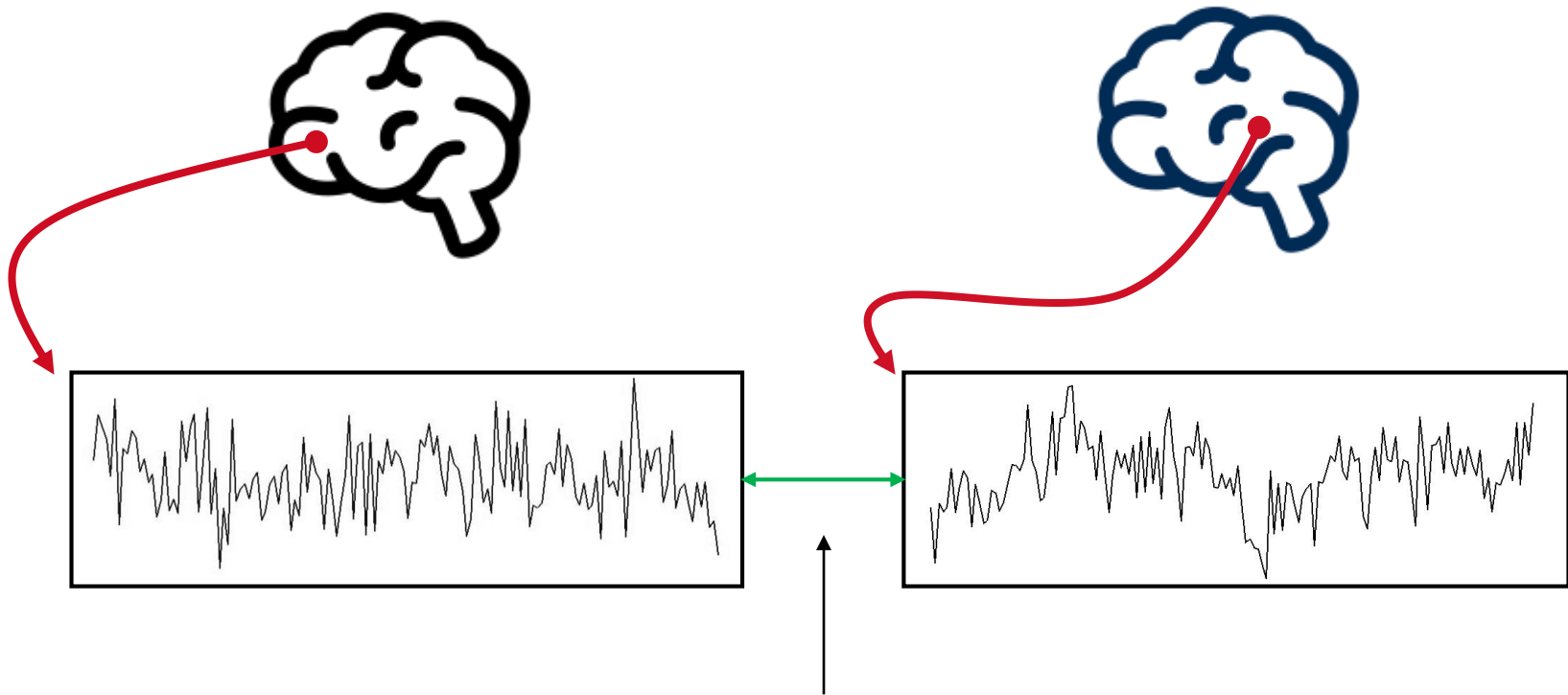


Increased false positive rates

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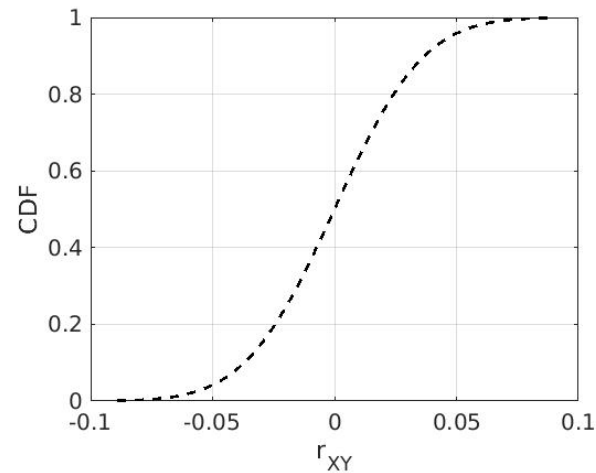
Ridiculous question: Does one patient's fMRI data influence another's?



correlation, mutual information, Granger causality, etc.

Test correlation against a t distribution...

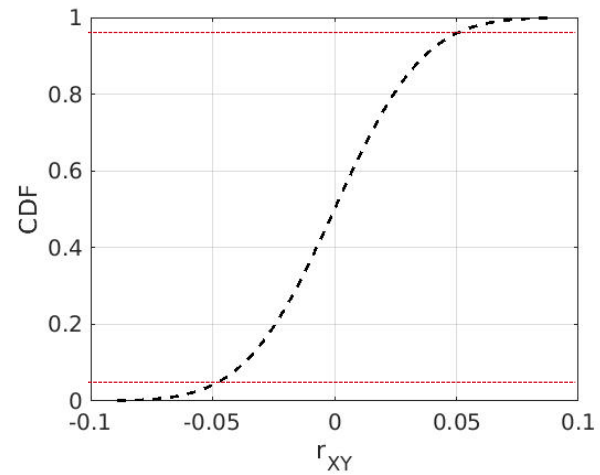
$$r_{XY} \sim t(N - 2)$$



Increased false positive rates

...at a nominal p-value of 5%

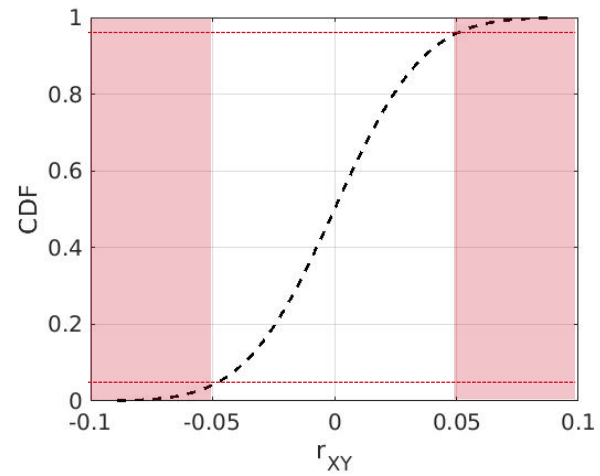
$$r_{XY} \sim t(N - 2)$$



Increased false positive rates

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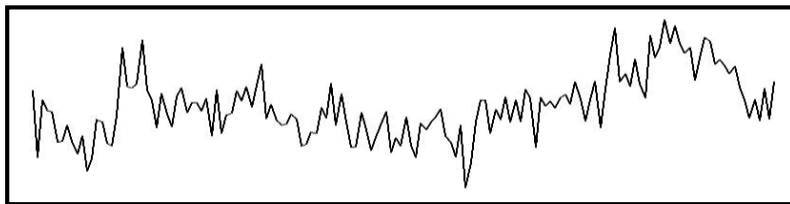
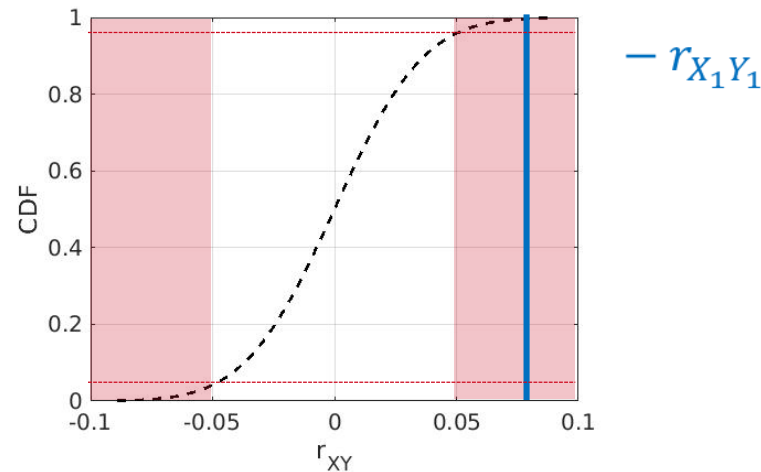
$$r_{XY} \sim t(N - 2)$$



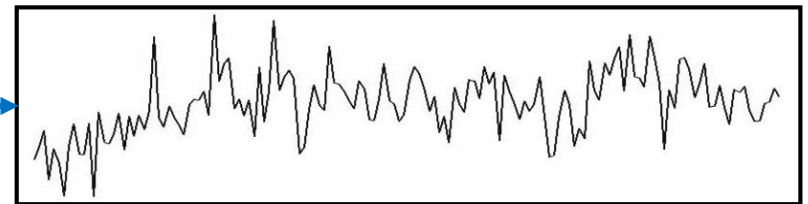
Increased false positive rates

Answer: 1/1 tests indicate true (100%)...

$$r_{XY} \sim t(N - 2)$$



X_1

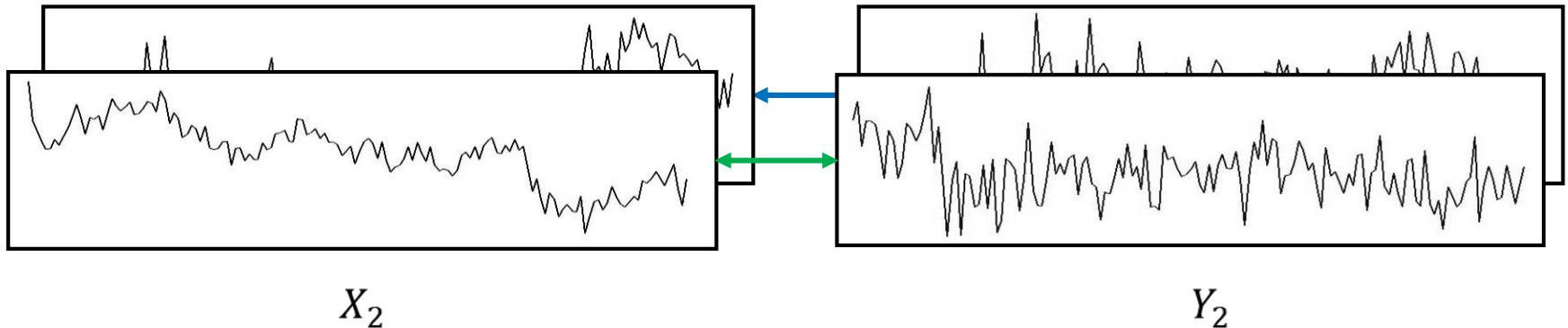
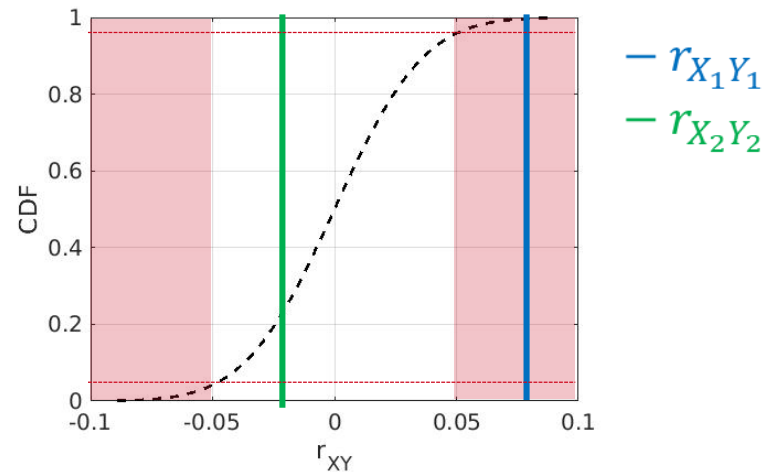


Y_1

Increased false positive rates

Answer: 1/2 tests indicate true (50%)...

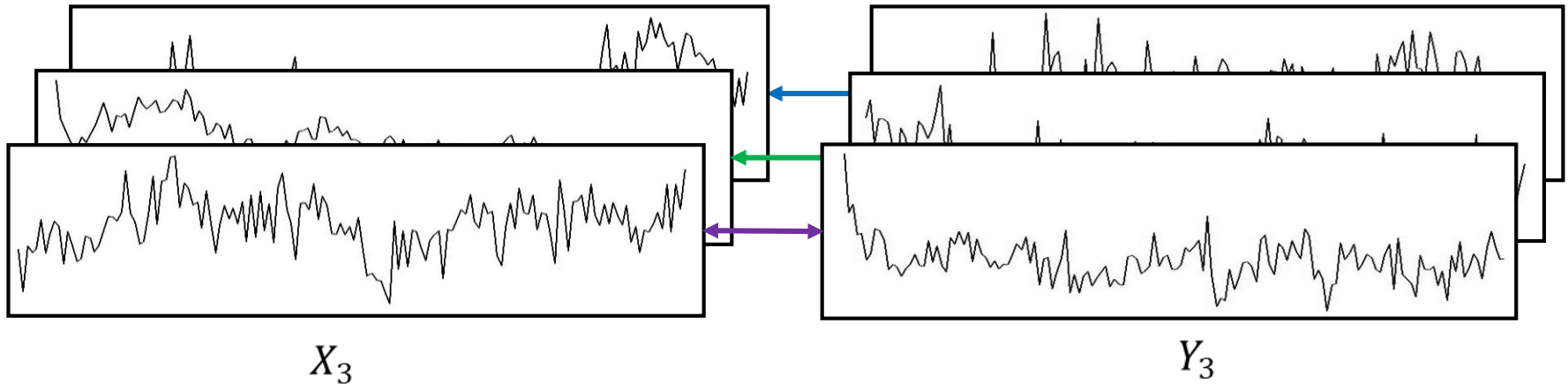
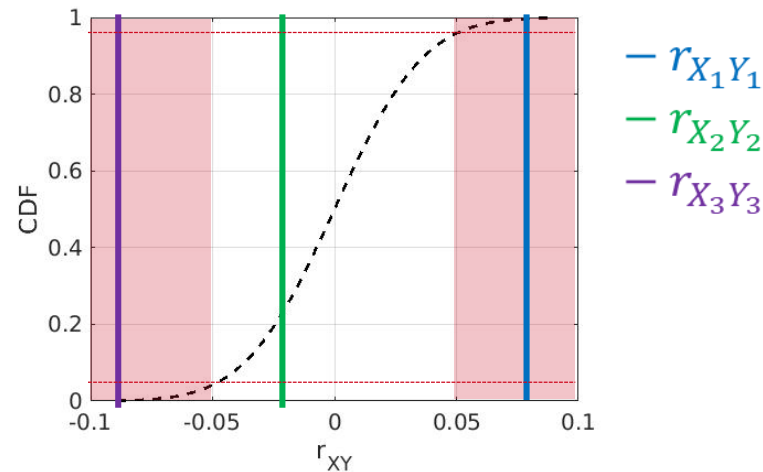
$$r_{XY} \sim t(N - 2)$$



Increased false positive rates

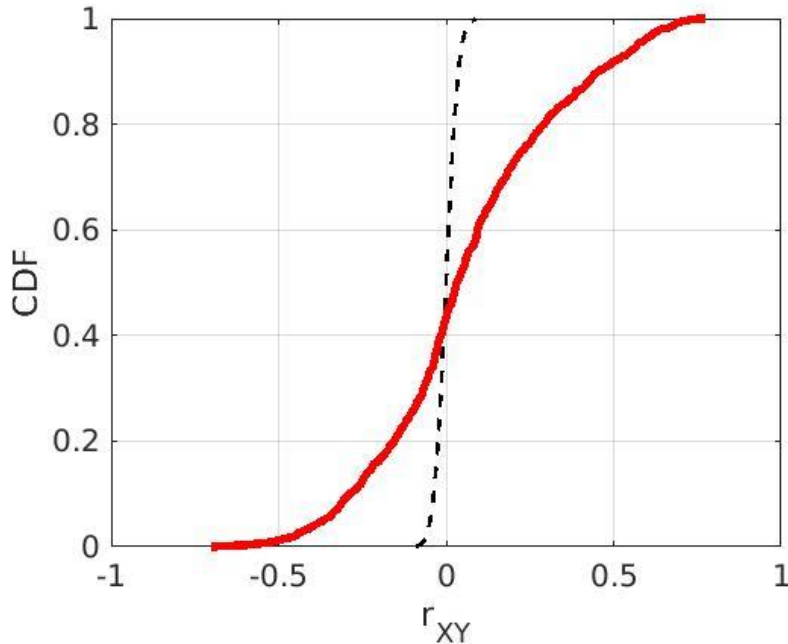
Answer: 2/3 tests indicate true (67%)...

$$r_{XY} \sim t(N - 2)$$



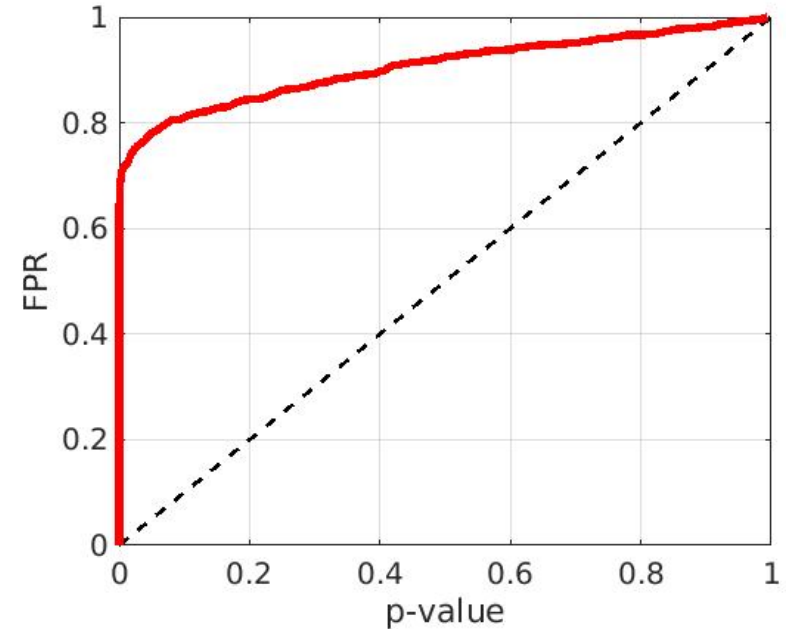
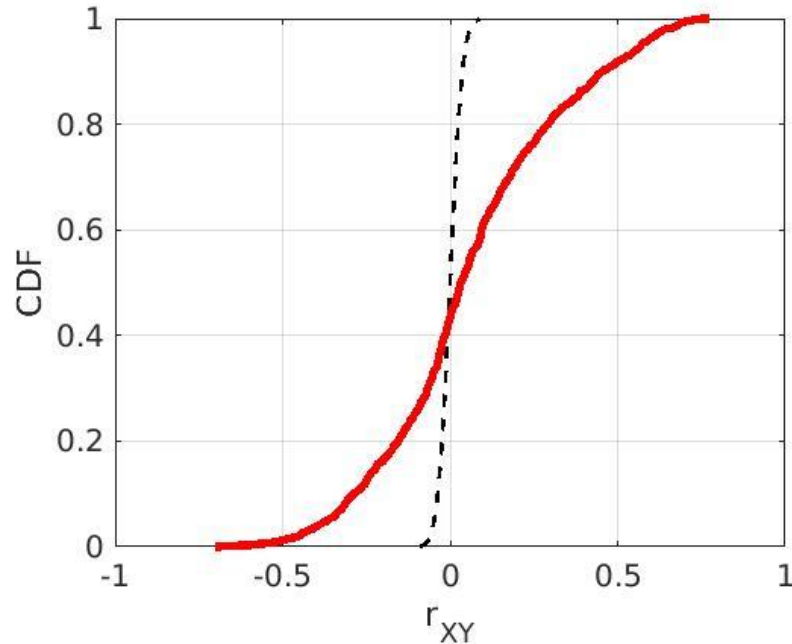
Increased false positive rates

Answer: 781/1000 tests indicate true (78%)



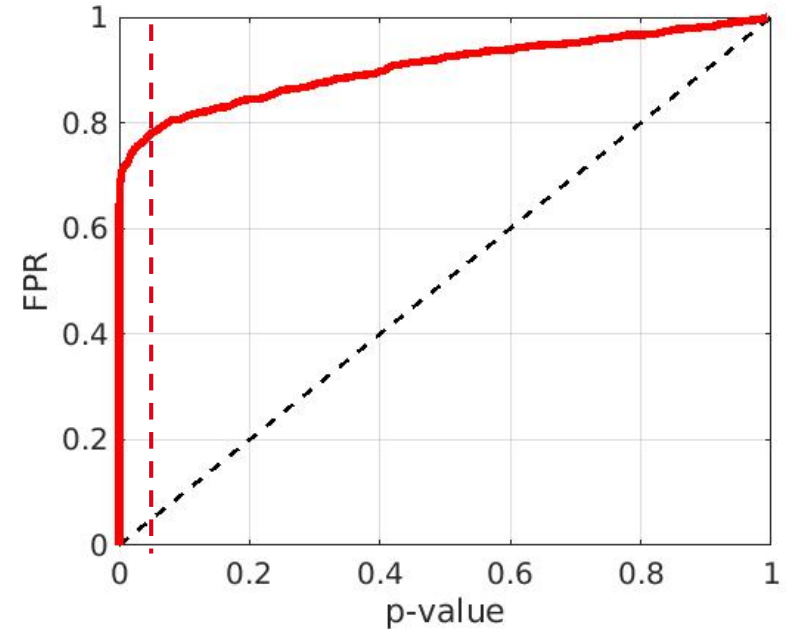
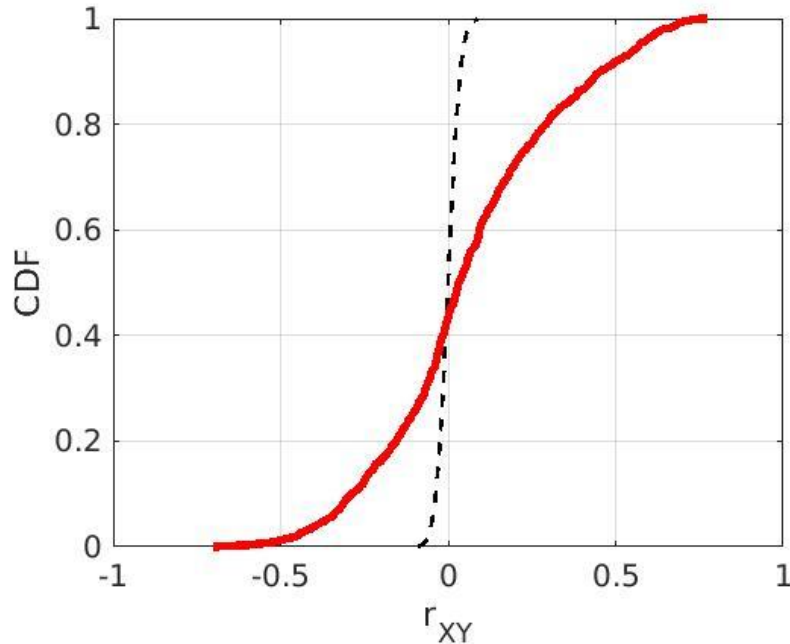
Increased false positive rates

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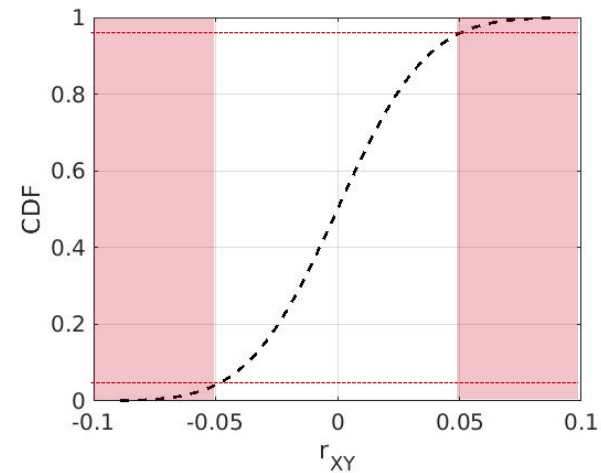


- › Higher autocorrelation increases the FPR of sample correlation
 - This has been known since Yule/Pearson's work in the early 20th century

- › How do we fix it?
 - **Bartlett's formula**
 - Correct the sample size based on autocorrelation of univariate signals
 - Does the process pass the t-test with effective sample size?
 - **Granger causality**
 - Define process through autocovariance
 - Does adding in another process improve predictability?

- › Testing Pearson correlation:

$$r_{XY} \sim t(N - 2)$$



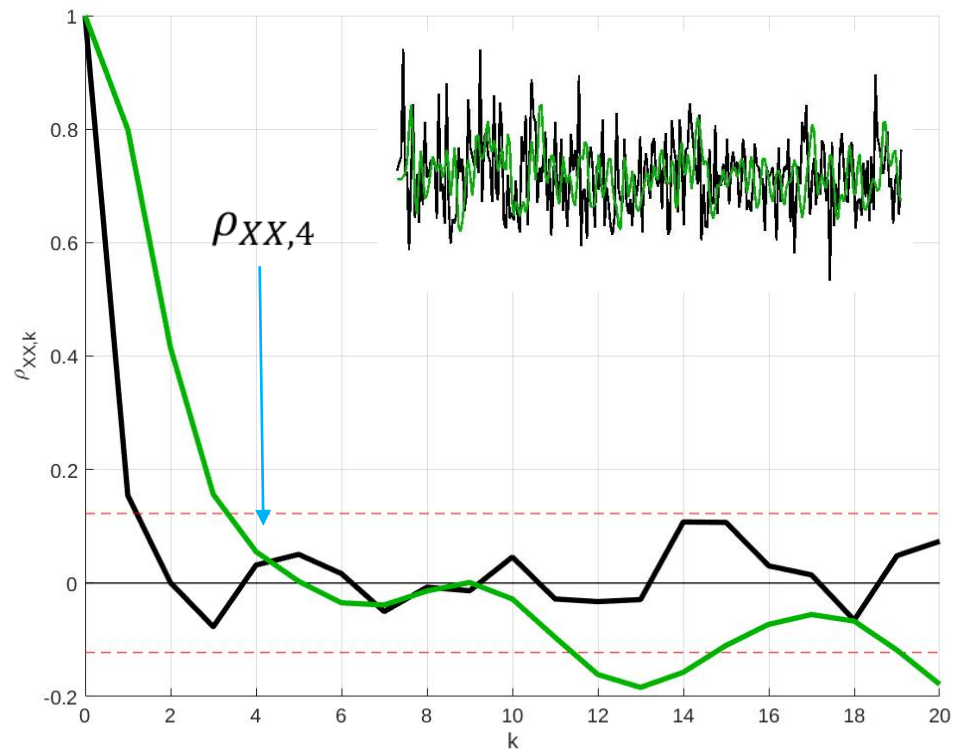
- › Testing Pearson correlation:

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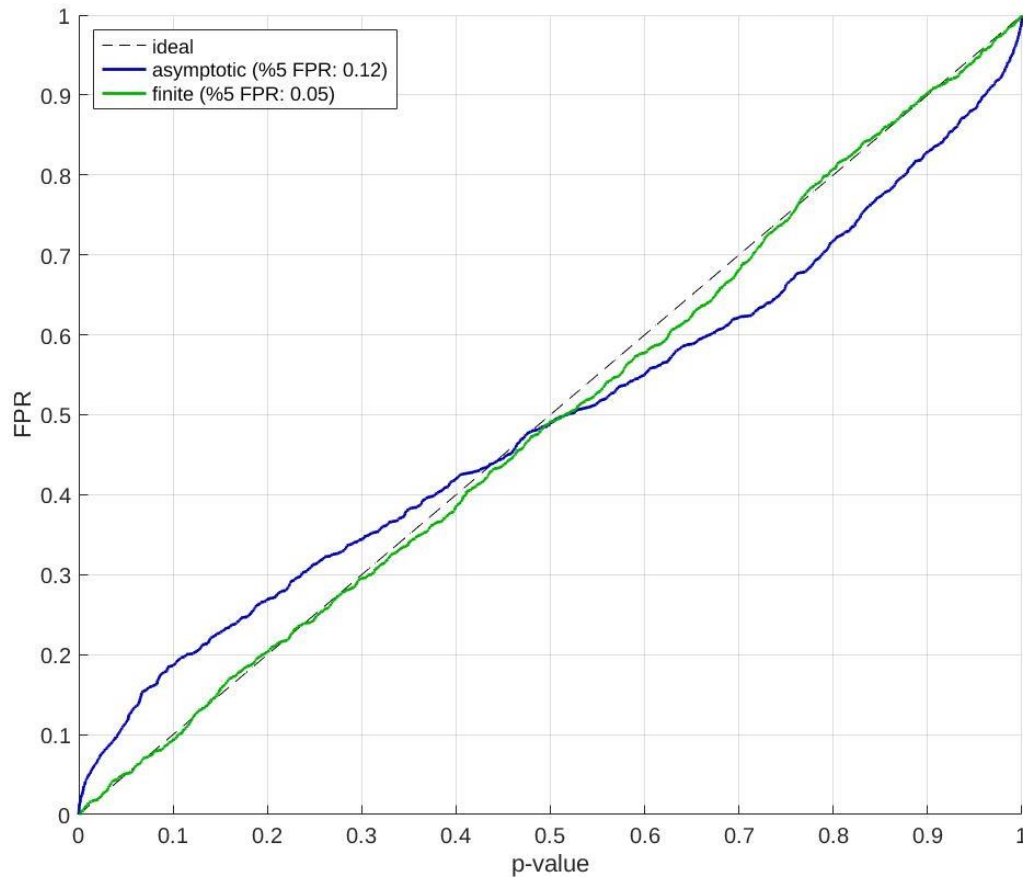
- › Under autocorrelation:

$$r_{XY} \sim t(N_{eff} - 2)$$

$$N_{eff} = \frac{N}{\sum_k \rho_{XX,k} \rho_{YY,k}}$$



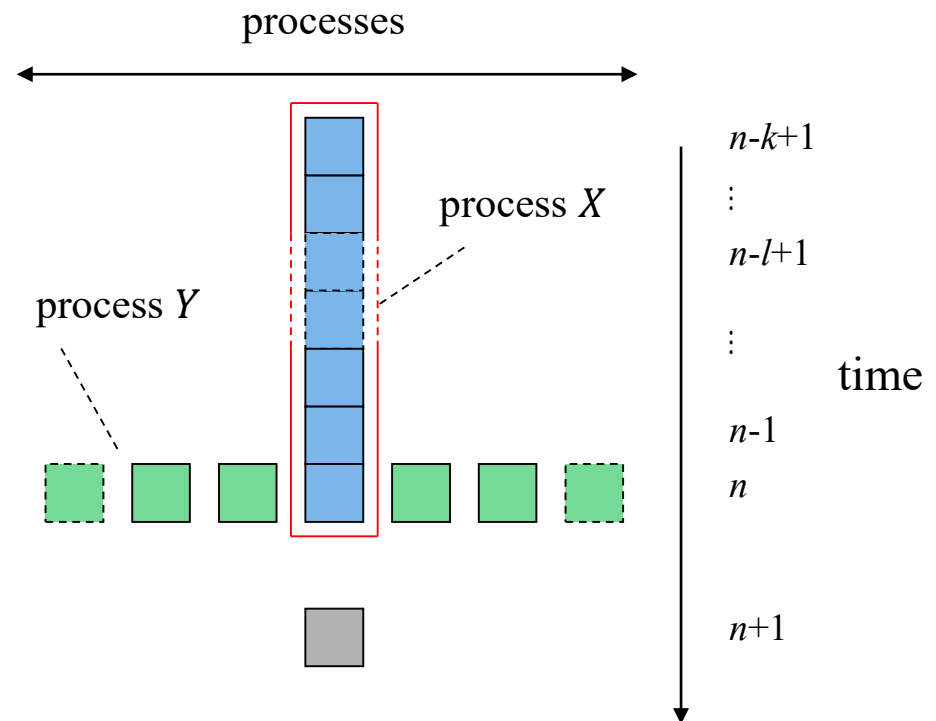
Bartlett's formula



- › Asymptotic distribution is **inefficient**
- › Bartlett's formula corrects to nominal FPR

› Build a target AR process

$$X_{n+1} = a_1 X_n + \cdots + a_k X_{n-k+1} + \epsilon_{1n}$$

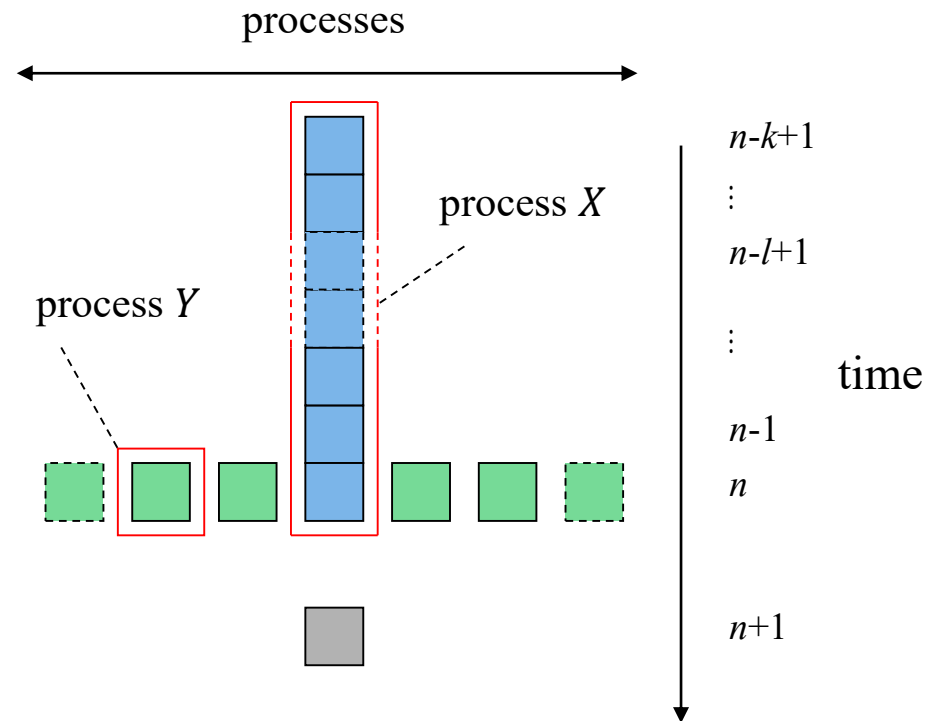


- › Build a target AR process

$$X_{n+1} = a_1 X_n + \dots + a_k X_{n-k+1} + \epsilon_{1n}$$

- › Include another (source) process

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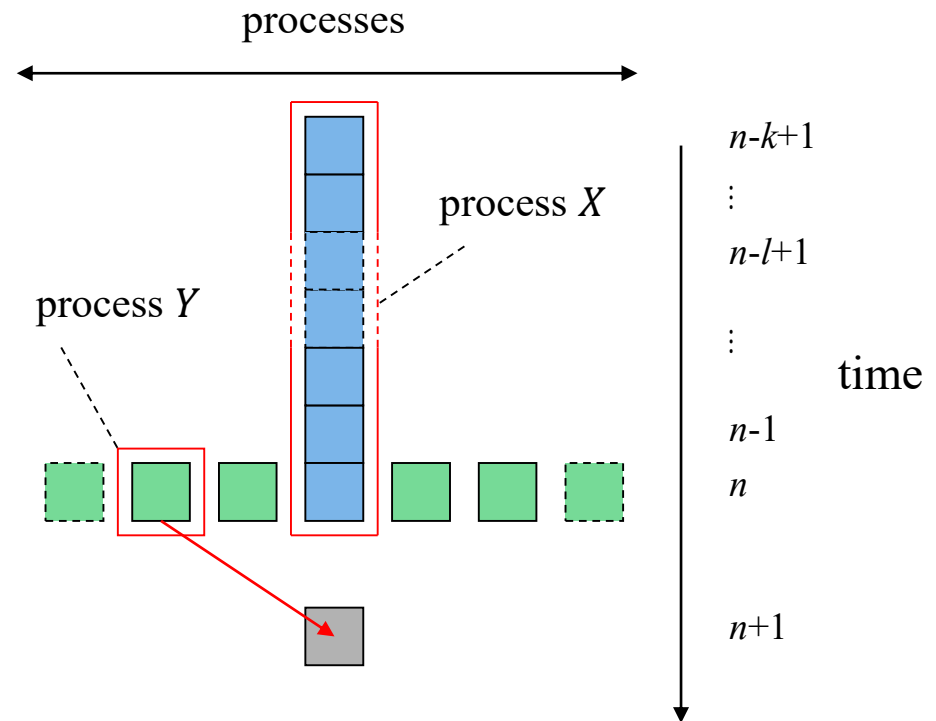
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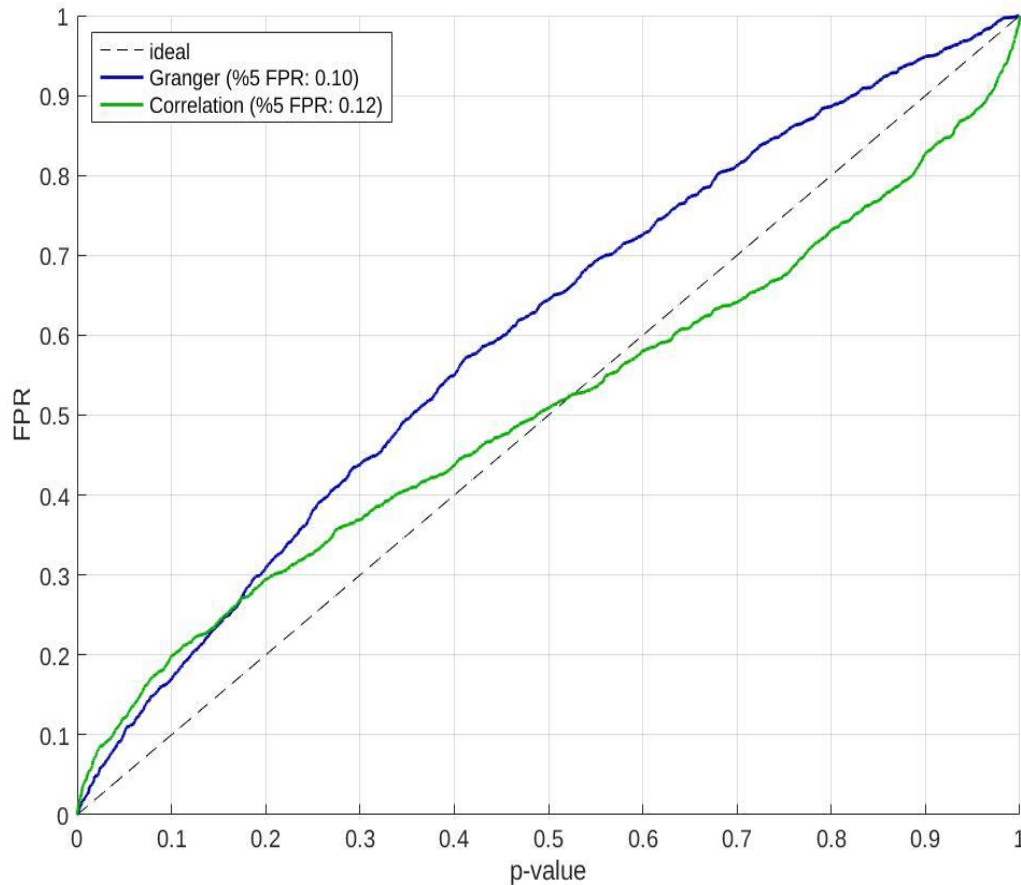
- › Test using Wilk's theorem:

$$N G_{Y \rightarrow X}(k, l) \sim \chi^2(l)$$

$$G_{Y \rightarrow X}(k, l) = \ln \left(\frac{\sum \epsilon_{1n}^2}{\sum \epsilon_{2n}^2} \right)$$



Granger causality



- › Asymptotic distribution is **biased**
- › Slightly lower FPR than correlation

Bartlett's formula and Granger causality

- › Bartlett's formula controls FPR for correlation with univariate processes
 - Multivariate generalization is known as canonical correlations
 - These are also inefficient under serial correlation

- › Granger causality reduces but does not control FPR
 - Naturally extends to multiple time series
 - FPR increases for:
 - more dimensions, or
 - higher order AR/filtering

Sampling distribution of Granger causality

- › How do we control for the FPR of Granger?
 - Granger causality is equivalent to **conditional mutual information** (Barnett et al., 2009)
 - In our paper, we show CMI for a univariate source and target can be expressed as a squared **partial correlation**
 - Bartlett's formula can be used to obtain the sampling distributions
 - Through chain rule, multivariate measures are sums of squared PC

Sampling distribution of partial correlation and CMI

- › Granger causality is partial correlation squared

$$G_{Y \rightarrow X}(1,1) = -\ln(1 - r_{X_{n+1}Y_n \cdot X_n}^2)$$

Sampling distribution of partial correlation and CMI

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$$G_{Y \rightarrow X}(1,1) = -\ln(1 - r_{X_{n+1}Y_n \cdot X_n}^2)$$

- › Partial correlation follows same distribution as correlation with less effective samples based on the number of conditionals

$$r_{X_{n+1}Y_n \cdot X_n} \sim t(N_{eff} - 3)$$

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$$r_{X_{n+1}Y_n \cdot X_n} \sim t(\underbrace{N_{eff}} - 3)$$

Bartlett's formula using residuals of
 $X_{n+1} \mid X_n$ and $Y_n \mid X_n$

Sampling distribution of partial correlation and CMI

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$$r_{X_{n+1}Y_n \cdot X_n} \sim t(N_{eff} - 3)$$

- › Squaring t-distribution gives an F-distribution

$$r_{X_{n+1}Y_n \cdot X_n}^2 \sim F(1, N_{eff} - 3)$$

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$$r_{X_{n+1}Y_n \cdot X_n}^2 \sim F(1, N_{eff} - 3)$$

- › This is the approximate sampling distribution of Granger (exact can be Monte Carlo sampled inside log)

$$G_{Y \rightarrow X}(1,1) \sim F(1, N_{eff} - 3)$$

- › By chain rule, increasing the source dimension simply adds more terms

$$G_{Y \rightarrow X}(k, l) \approx r^2_{X_{n+1}Y_n \cdot X_n^{(k)}} + r^2_{X_{n+1}Y_{n-1} \cdot \{X_n^{(k)}, Y_n\}} + \cdots + r^2_{X_{n+1}Y_{n-l+1} \cdot \{X_n^{(k)}, Y_n, \dots, Y_{n-l+2}\}}$$

Multivariate Granger causality

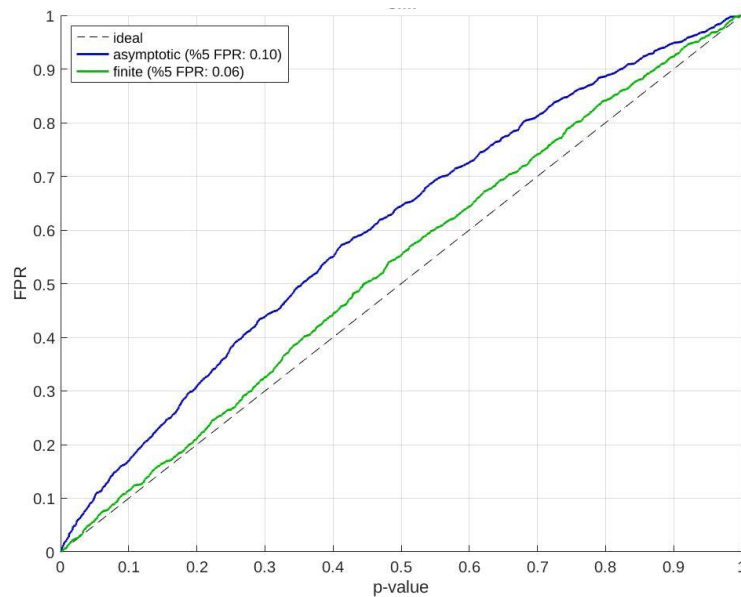
- By chain rule, increasing the source dimension simply adds more terms

$$G_{Y \rightarrow X}(k, l) \approx \underbrace{r^2_{X_{n+1}Y_n \cdot X_n^{(k)}}}_{F(1, N_{eff,1} - k - 2)} + \underbrace{r^2_{X_{n+1}Y_{n-1} \cdot \{X_n^{(k)}, Y_n\}}}_{F(1, N_{eff,2} - k - 1 - 2)} + \cdots + \underbrace{r^2_{X_{n+1}Y_{n-l+1} \cdot \{X_n^{(k)}, Y_n, \dots, Y_{n-l+2}\}}}_{F(1, N_{eff,l} - k - l - 2)}$$

- These terms have different DOFs, and we Monte Carlo sample the distribution

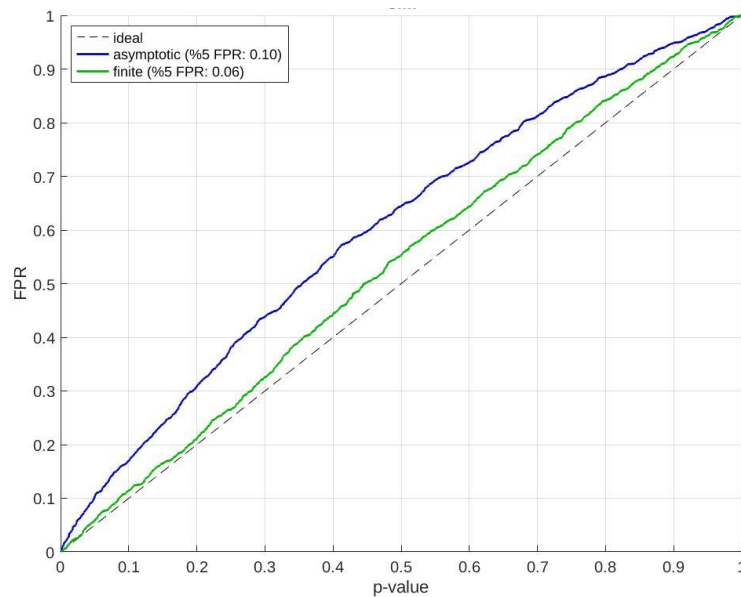
Simulate with $N=512$, inducing autoregression through **FIR filter**

~8th Order AR
(8th Order FIR filter)

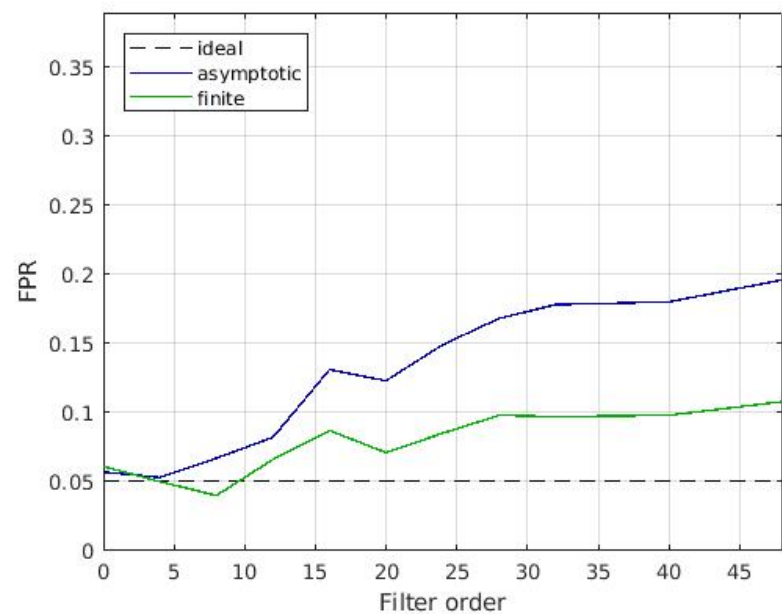


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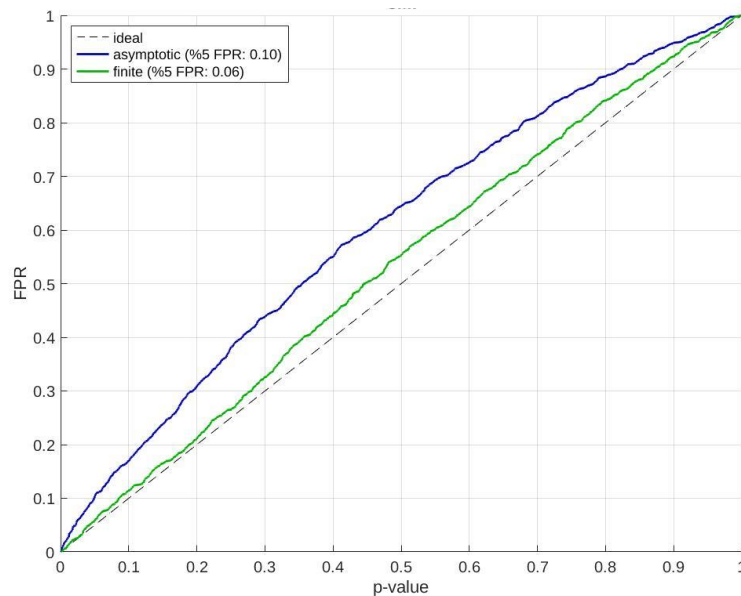


Increasing filter order

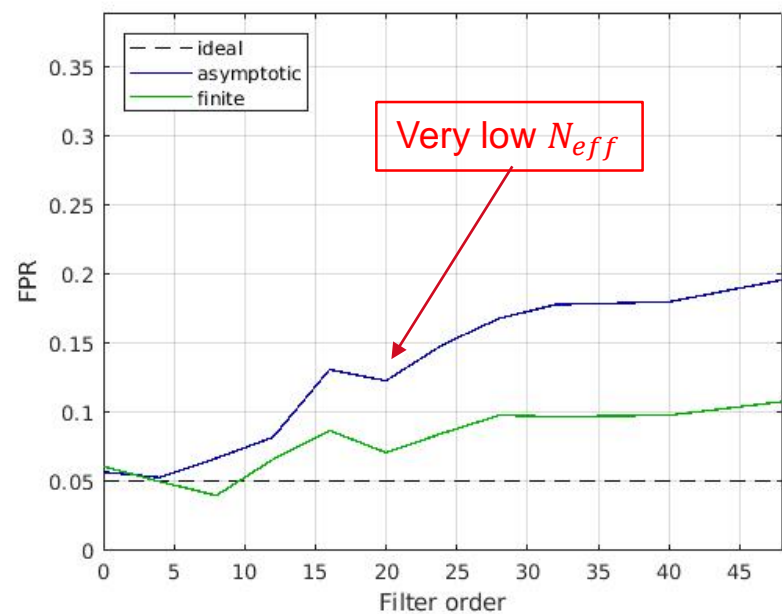


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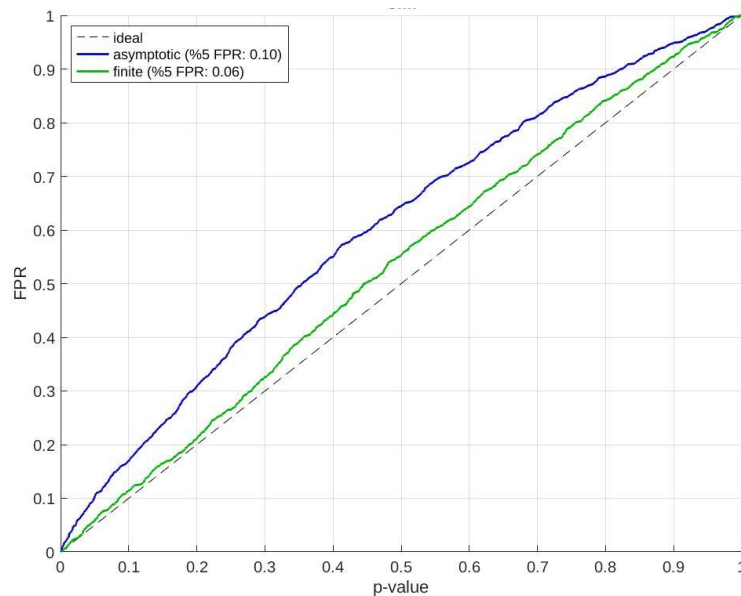


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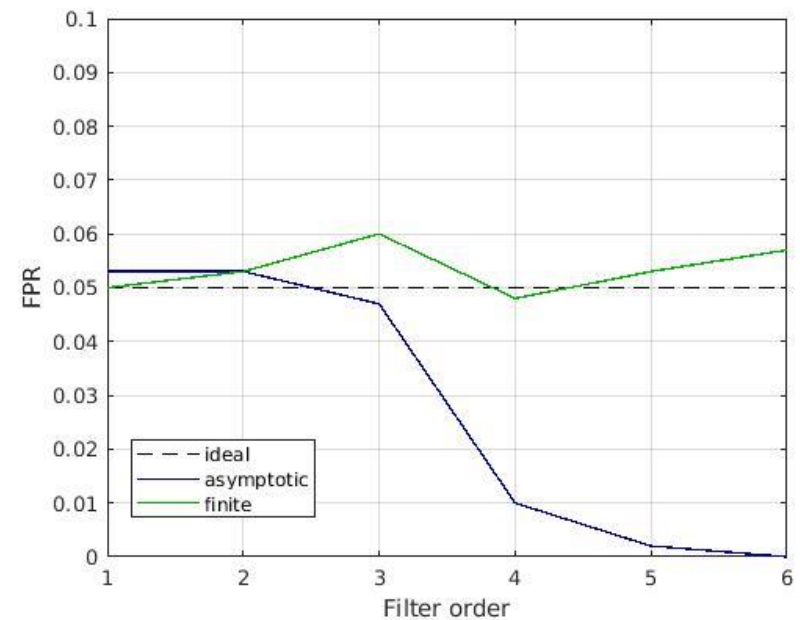


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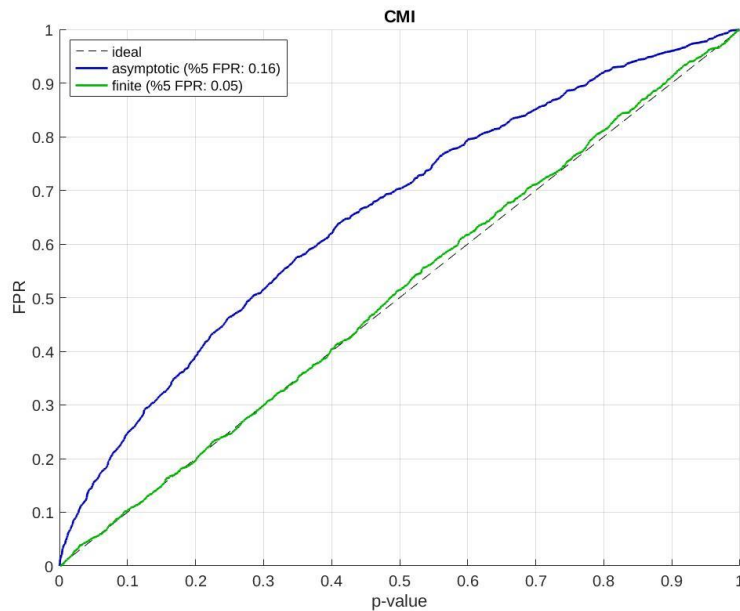


Increasing dimensionality



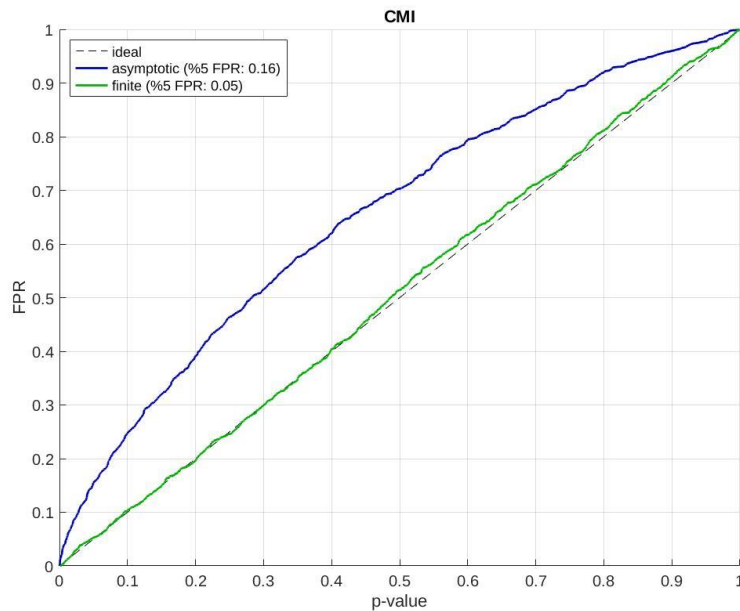
Simulate with $N=512$, inducing autoregression through **IIR filter**

~16th Order AR
(4th Order IIR filter)

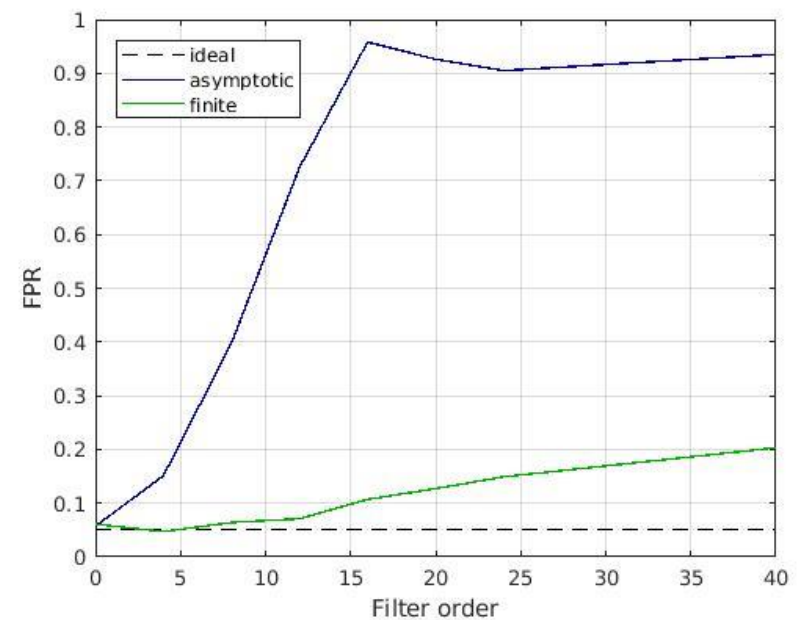


Simulate with $N=512$, inducing autoregression through **IIR filter**

~16th Order AR
(4th Order IIR filter)

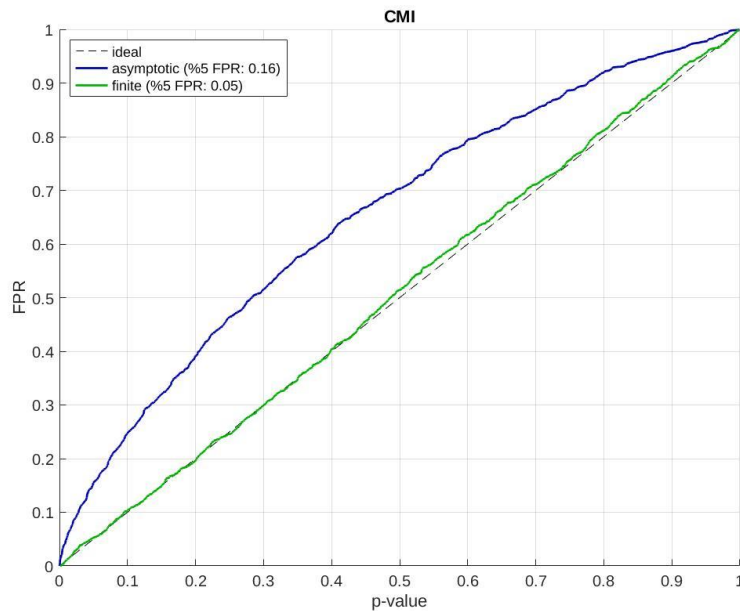


Increasing filter order



Simulate with $N=512$, inducing autoregression through **IIR filter**

~16th Order AR
(4th Order IIR filter)



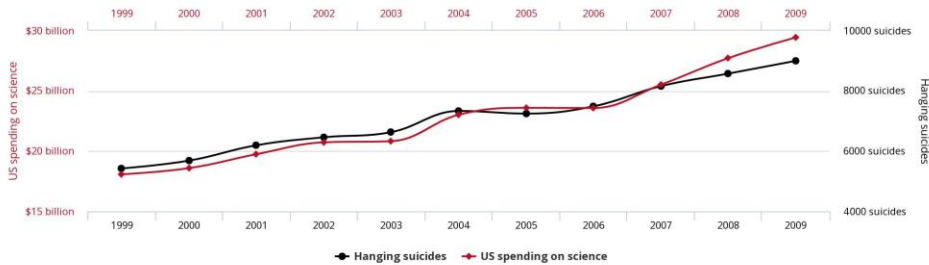
Increasing filter order



- › Important dependence measures exhibit bias for autocorrelated Gaussian processes
- › These measures can be represented as sums of squared partial correlations
- › This representation allows us to derive the sampling distribution
- › Before our work, these distributions were only valid asymptotically

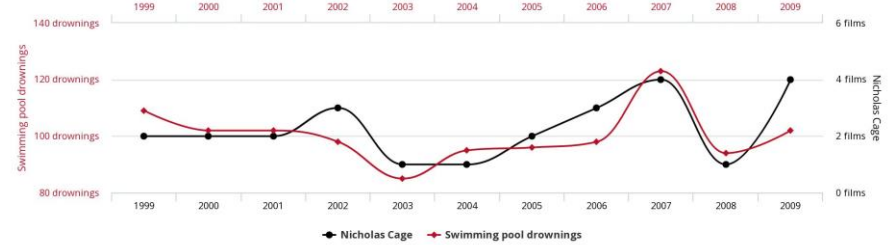
Thank you!

US spending on science, space, and technology
correlates with
Suicides by hanging, strangulation and suffocation



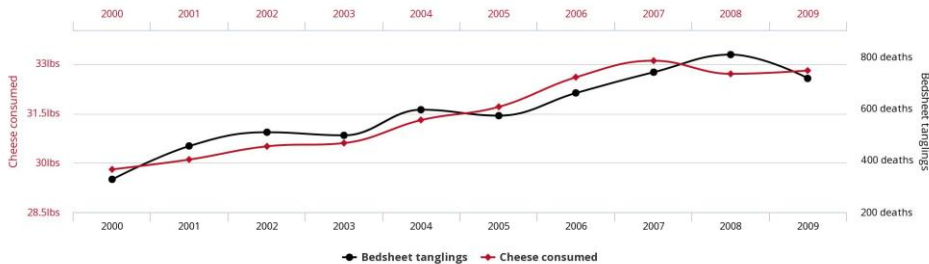
tylervigen.com

Number of people who drowned by falling into a pool
correlates with
Films Nicolas Cage appeared in



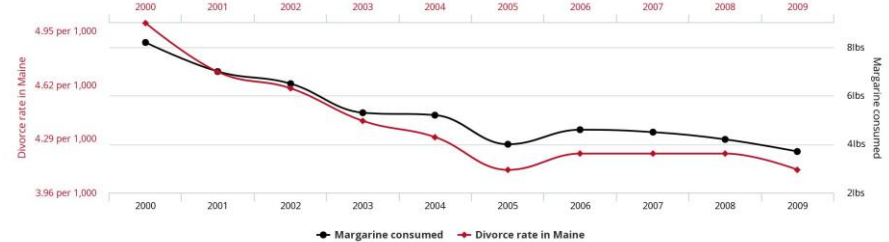
tylervigen.com

Per capita cheese consumption
correlates with
Number of people who died by becoming tangled in their bedsheets



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Divorce rate in Maine
correlates with
Per capita consumption of margarine



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