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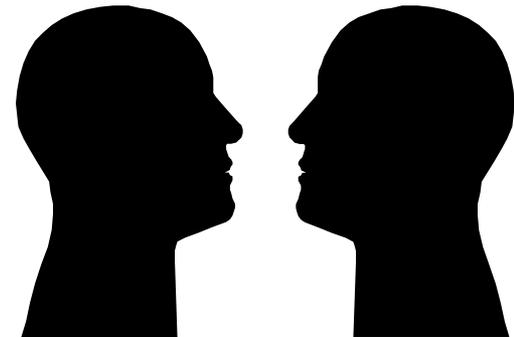
CPSC 641: Network Traffic Self-Similarity

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- A classic network traffic measurement study has shown that aggregate Ethernet LAN traffic is self-similar [Leland et al 1993]
- A statistical property that is very different from the traditional Poisson-based models
- This presentation: definition of network traffic self-similarity, Bellcore Ethernet LAN data, implications of self-similarity



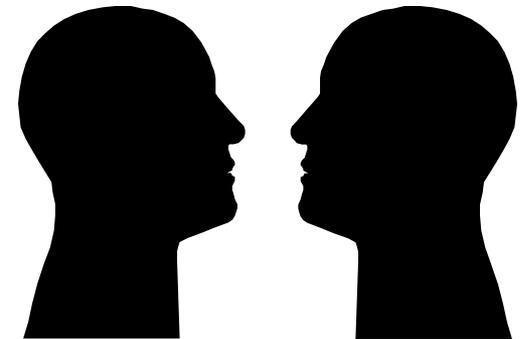
- Collected lengthy traces of Ethernet LAN traffic on Ethernet LAN(s) at Bellcore
- High resolution time stamps
- Analyzed statistical properties of the resulting time series data
- Each observation represents the number of packets (or bytes) observed per time interval (e.g., 10 4 8 12 7 2 0 5 17 9 8 8 2...)

- If you plot the number of packets observed per time interval as a function of time, then the plot looks “similar” regardless of what interval size you choose
- E.g., 10 msec, 100 msec, 1 sec, 10 sec,...
- Same applies if you plot number of bytes observed per interval of time

- In other words, self-similarity implies a “fractal-like” behaviour: no matter what time scale you use to examine the data, you see similar patterns
- Implications:
 - Burstiness exists across many time scales
 - No natural length of a burst
 - Traffic does not necessarily get “smoother” when you aggregate it (unlike Poisson traffic)

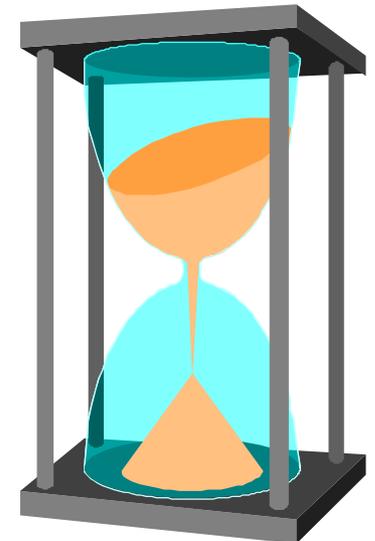
- Self-similarity is a rigorous statistical property (i.e., a lot more to it than just the pretty “fractal-like” pictures)
- Assumes you have time series data with finite mean and variance (i.e., covariance stationary stochastic process)
- Must be a very long time series (infinite is best!)
- Can test for presence of self-similarity

- Self-similarity manifests itself in several equivalent fashions:
- Slowly decaying variance
- Long range dependence
- Non-degenerate autocorrelations
- Hurst effect

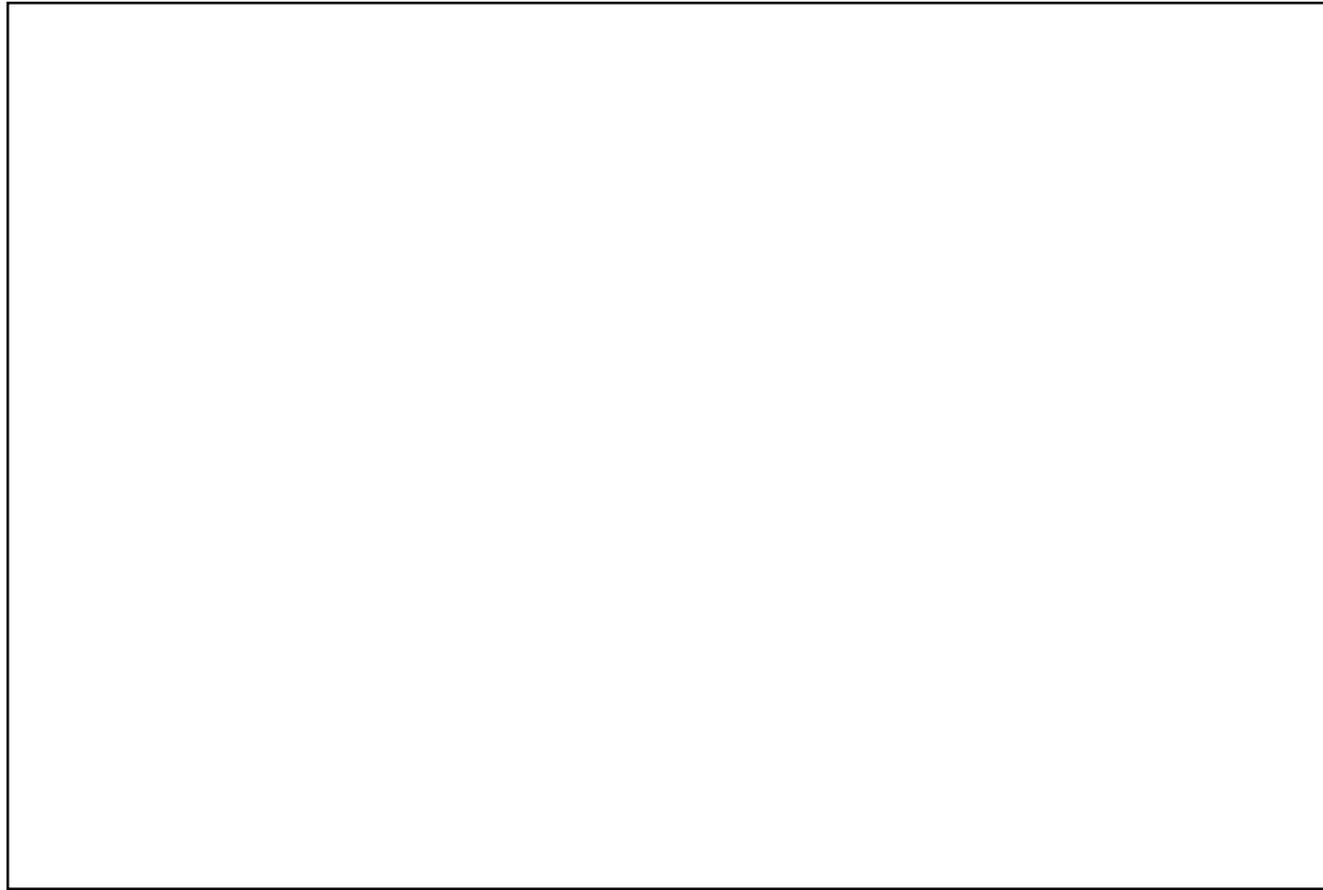


- The variance of the sample decreases more slowly than the reciprocal of the sample size
- For most processes, the variance of a sample diminishes quite rapidly as the sample size is increased, and stabilizes soon
- For self-similar processes, the variance decreases very slowly, even when the sample size grows quite large

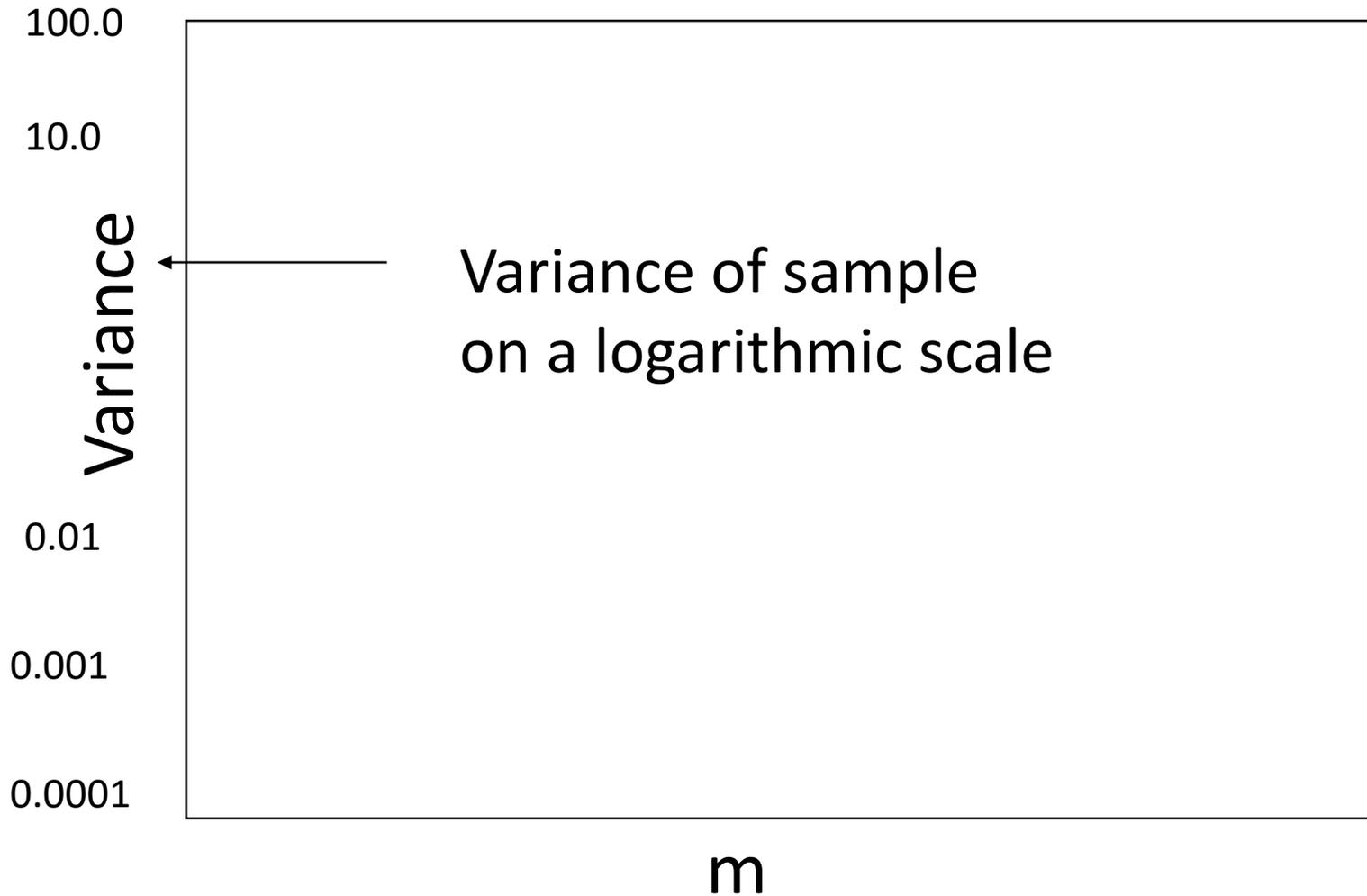
- The “variance-time plot” is one method to test for the slowly decaying variance property
- Plots the variance of the sample versus the sample size, on a log-log plot
- For most processes, the result is a straight line with slope -1
- For self-similar, the line is much flatter



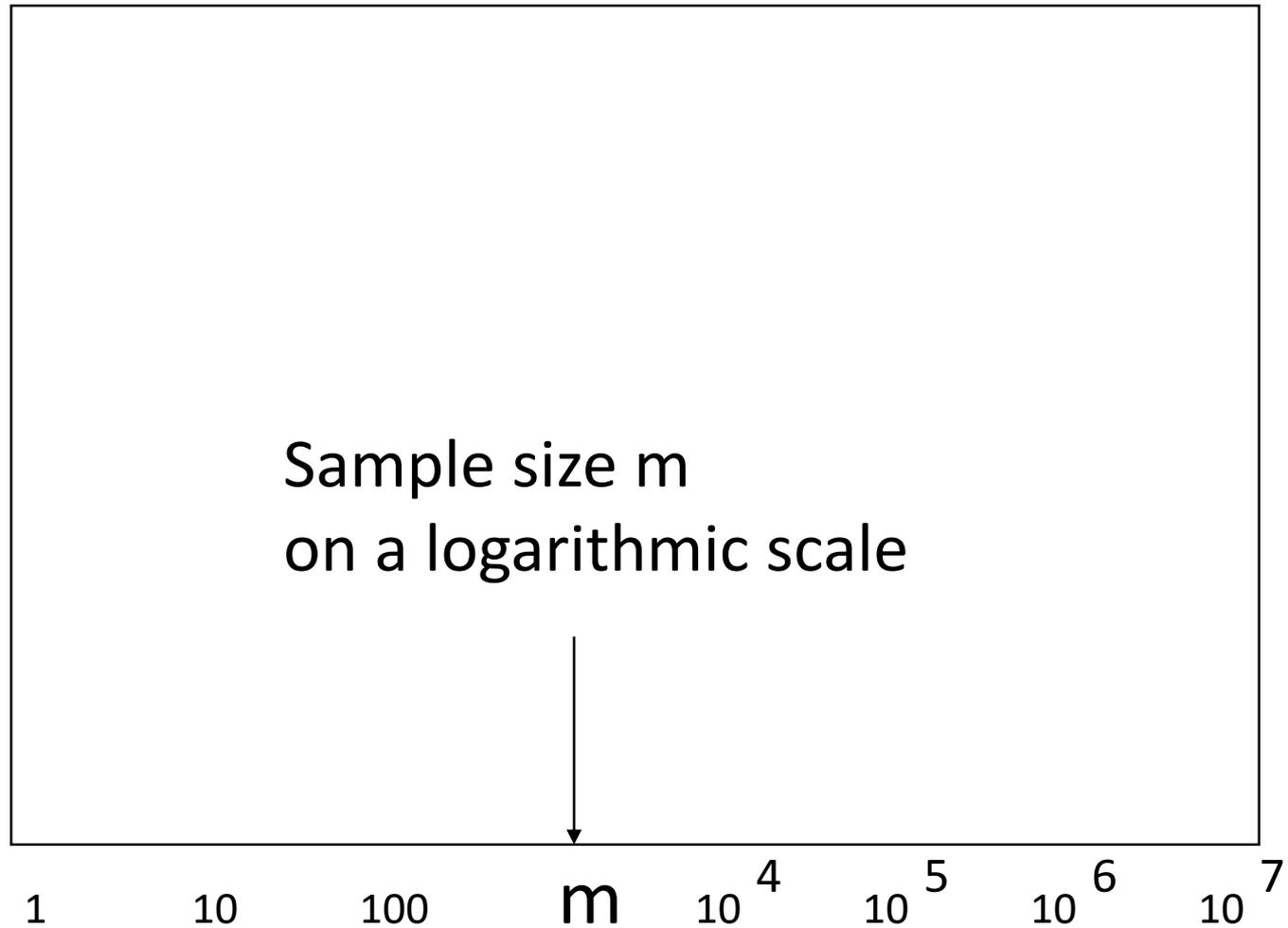
Variance



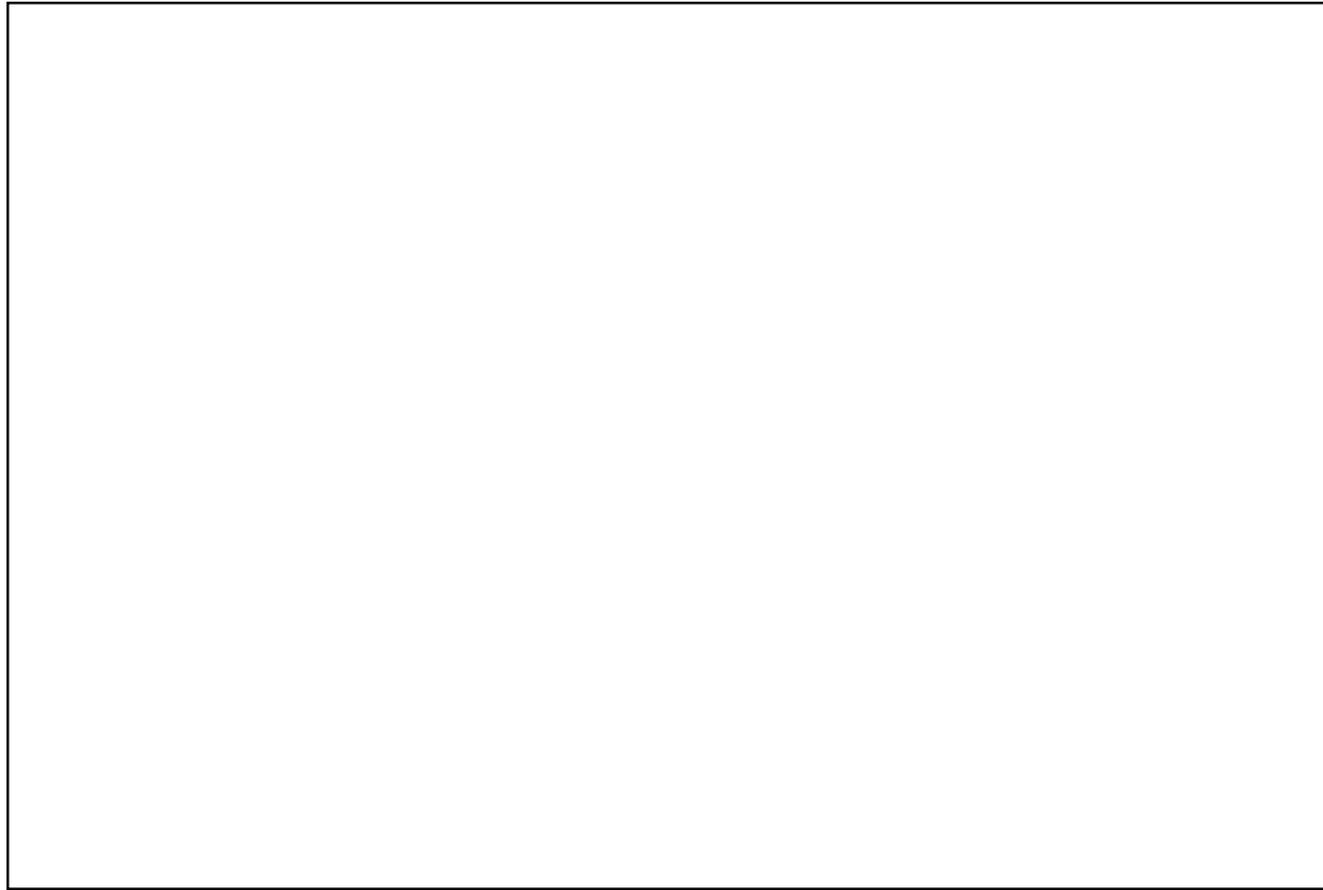
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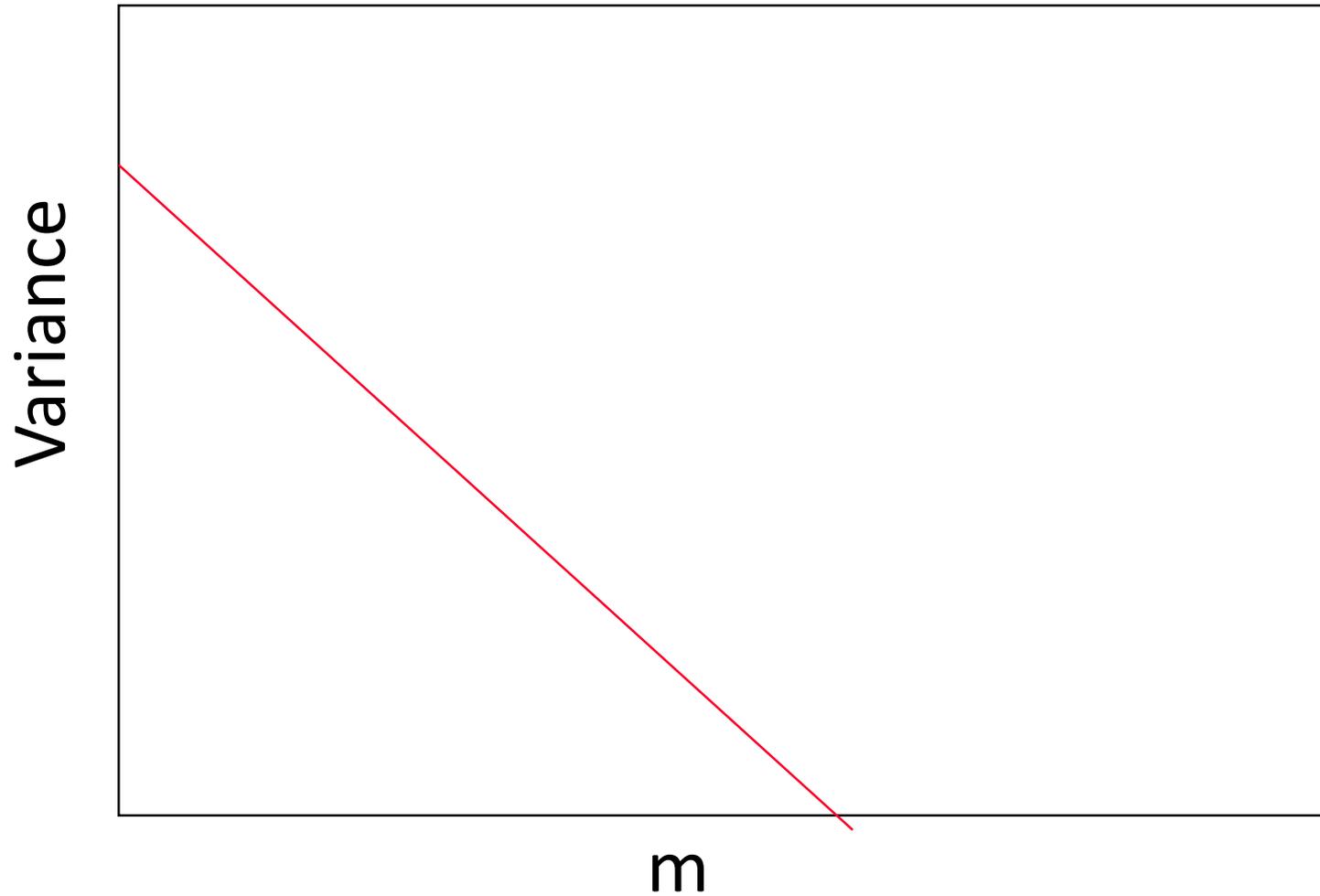
Variance

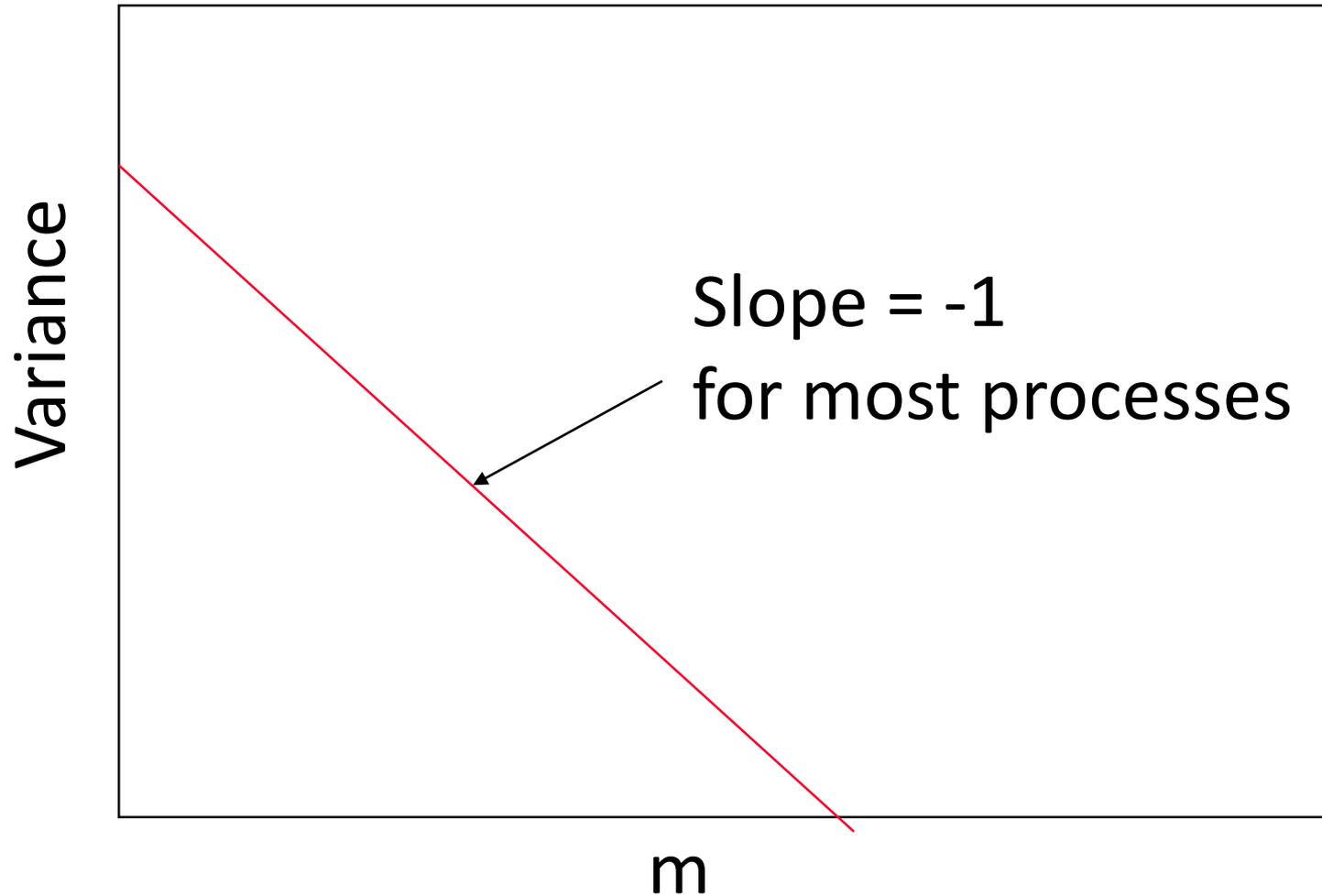


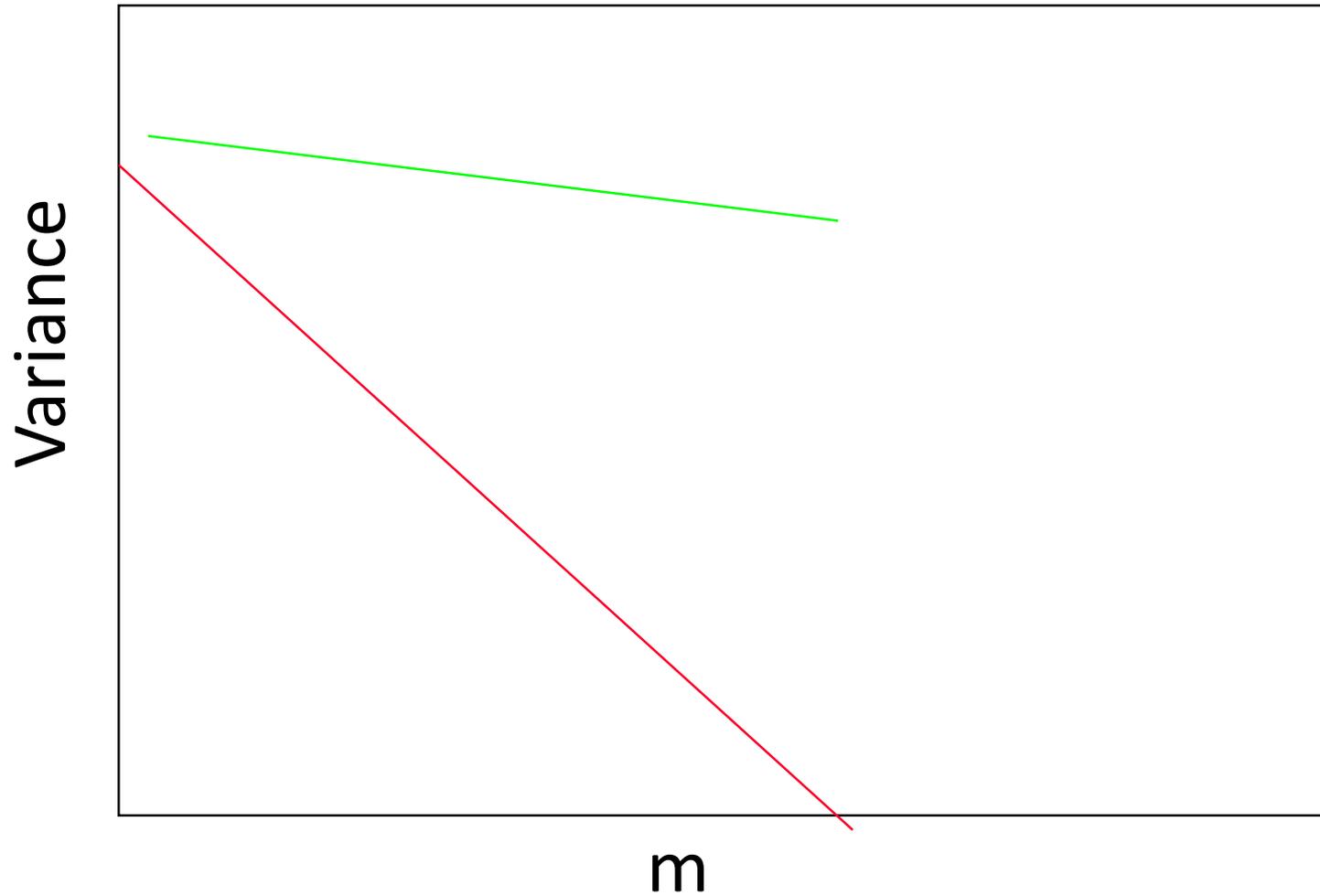
Variance

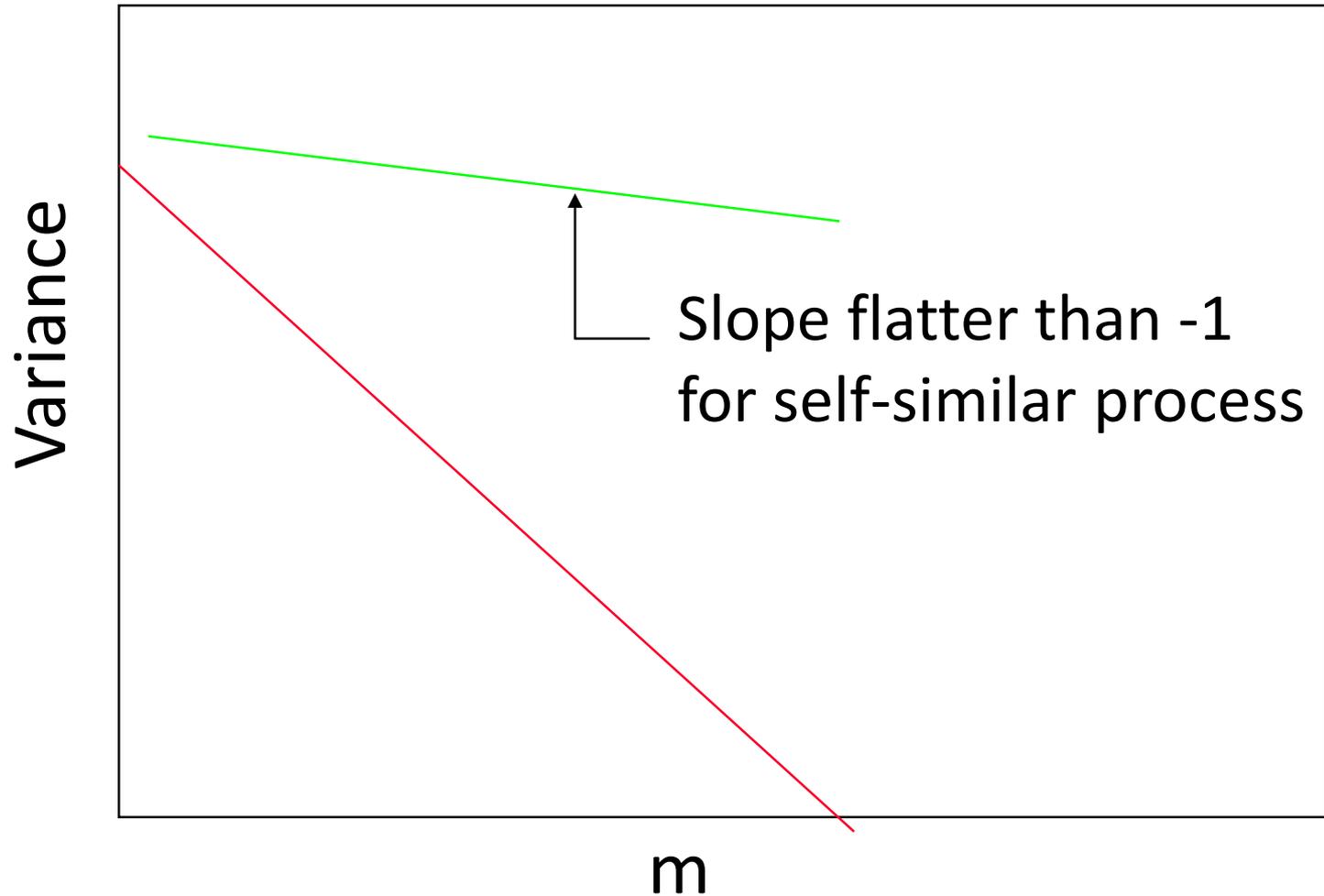


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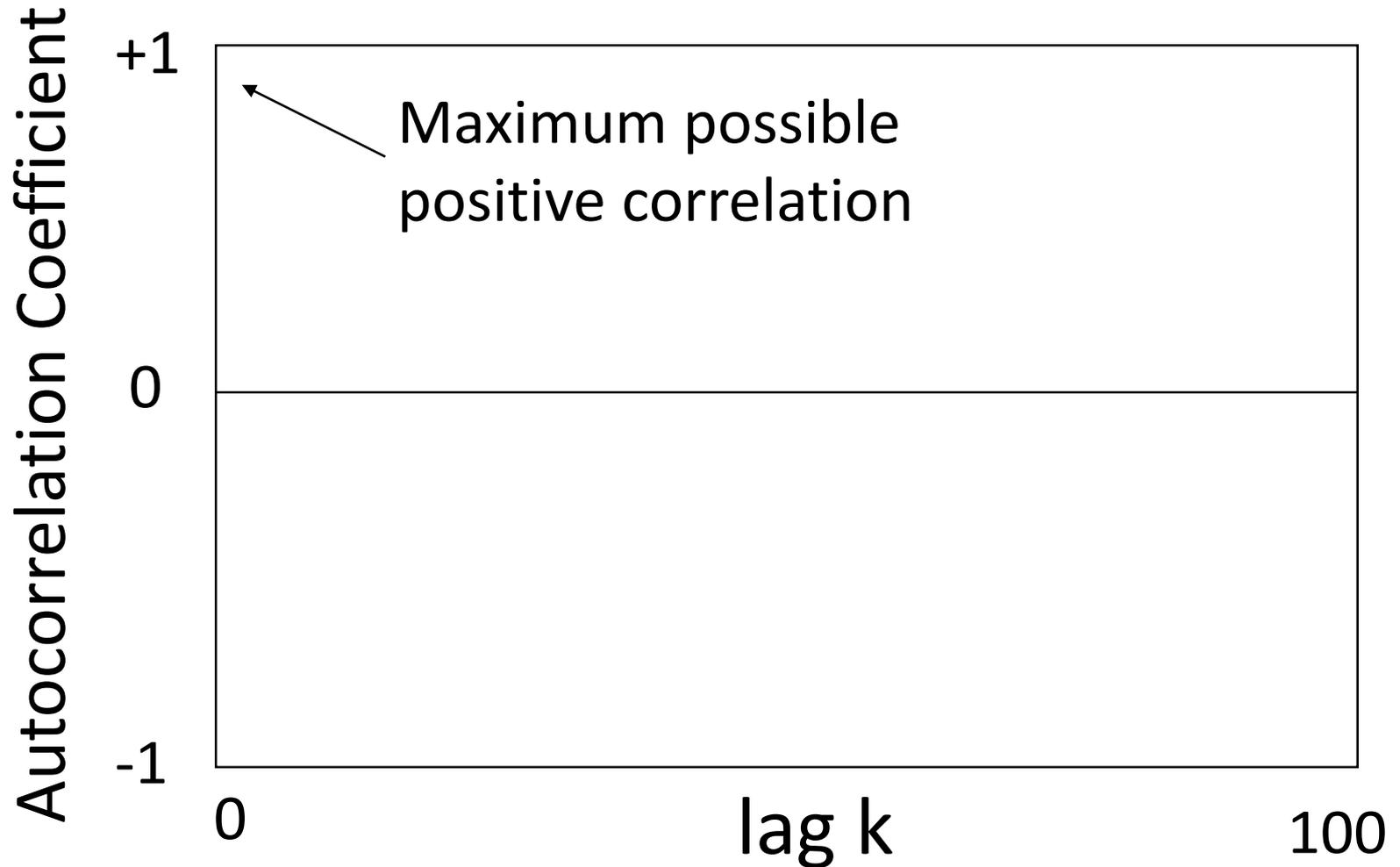


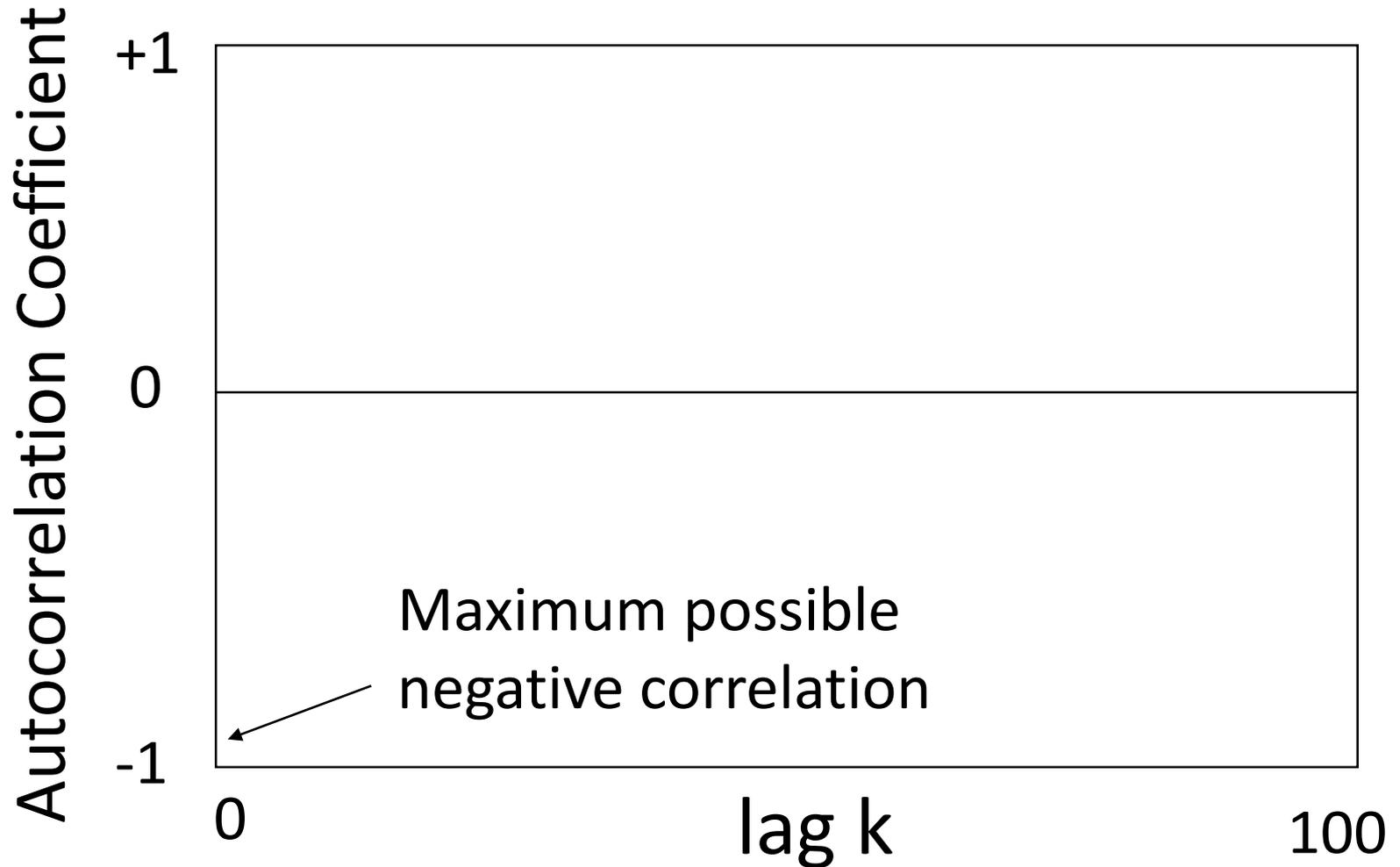
- Correlation is a statistical measure of the relationship, if any, between two random variables
- Positive correlation: both behave similarly
- Negative correlation: behave in opposite fashion
- No correlation: behaviour of one is statistically unrelated to behaviour of other

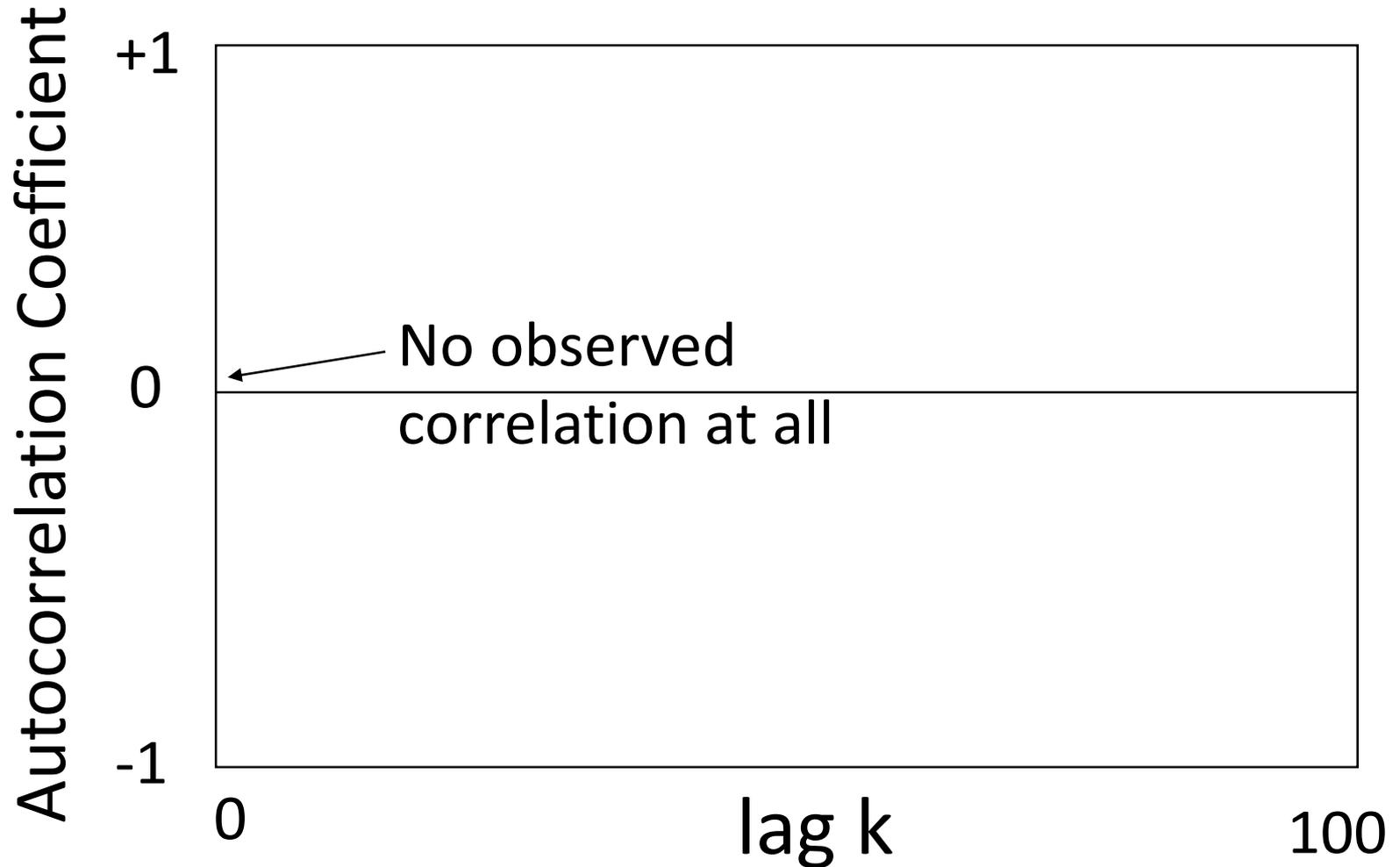
- Autocorrelation is a statistical measure of the relationship, if any, between a random variable and itself, at different time lags
- Positive correlation: big observation usually followed by another big, or small by small
- Negative correlation: big observation usually followed by small, or small by big
- No correlation: observations unrelated

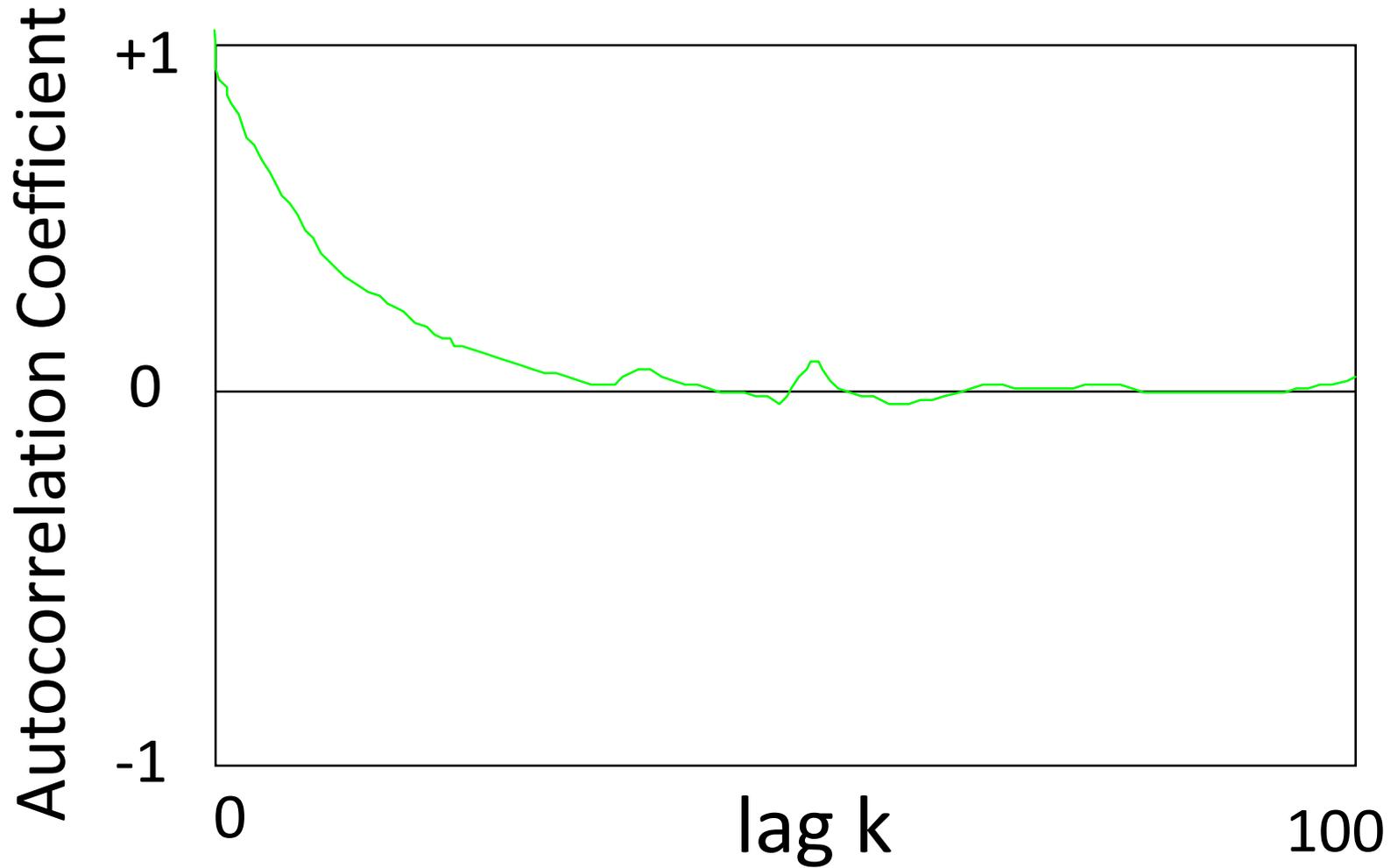
- Autocorrelation coefficient can range between +1 (very high positive correlation) and -1 (very high negative correlation)
- Zero means no correlation
- Autocorrelation function shows the value of the autocorrelation coefficient for different time lags k

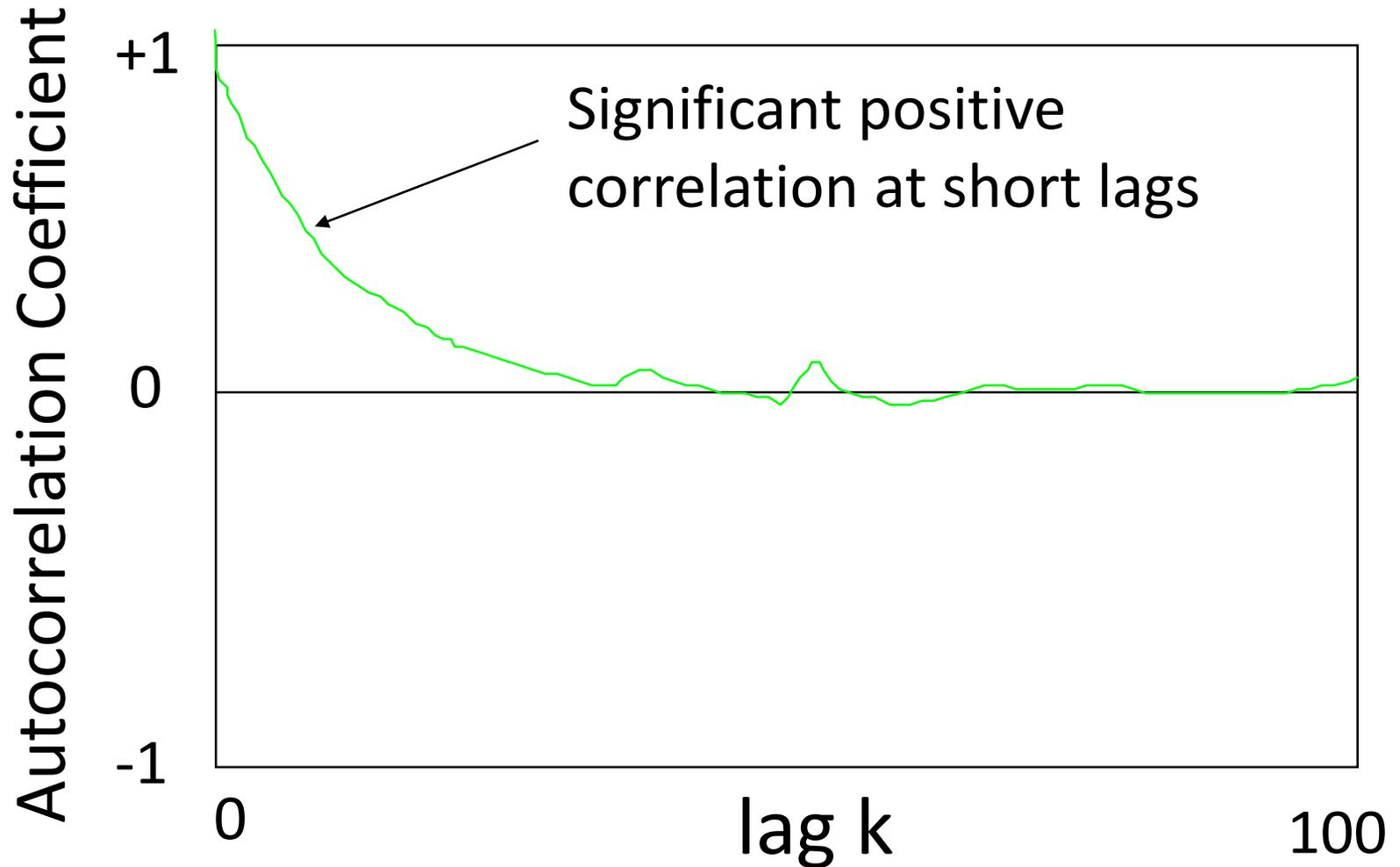


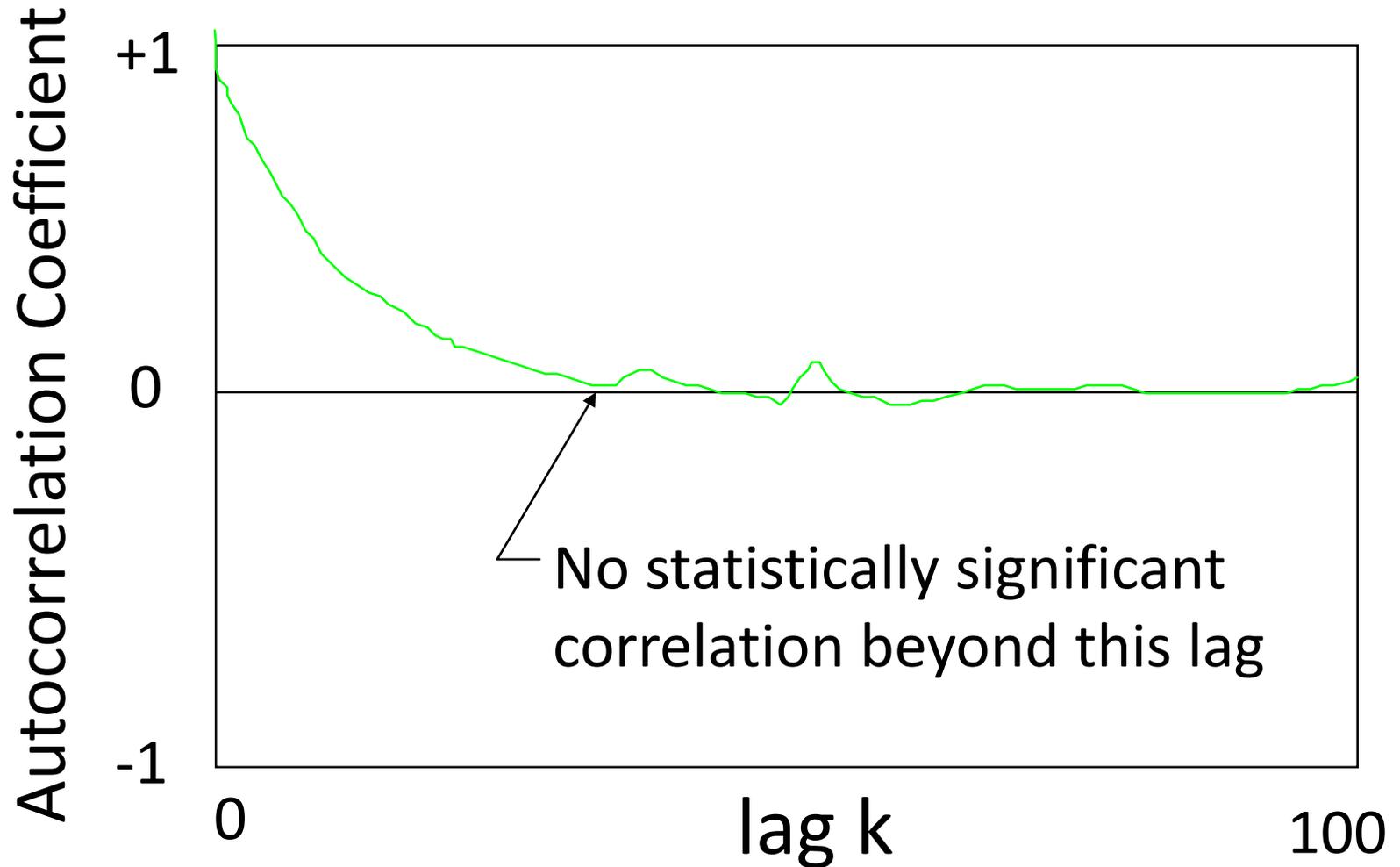




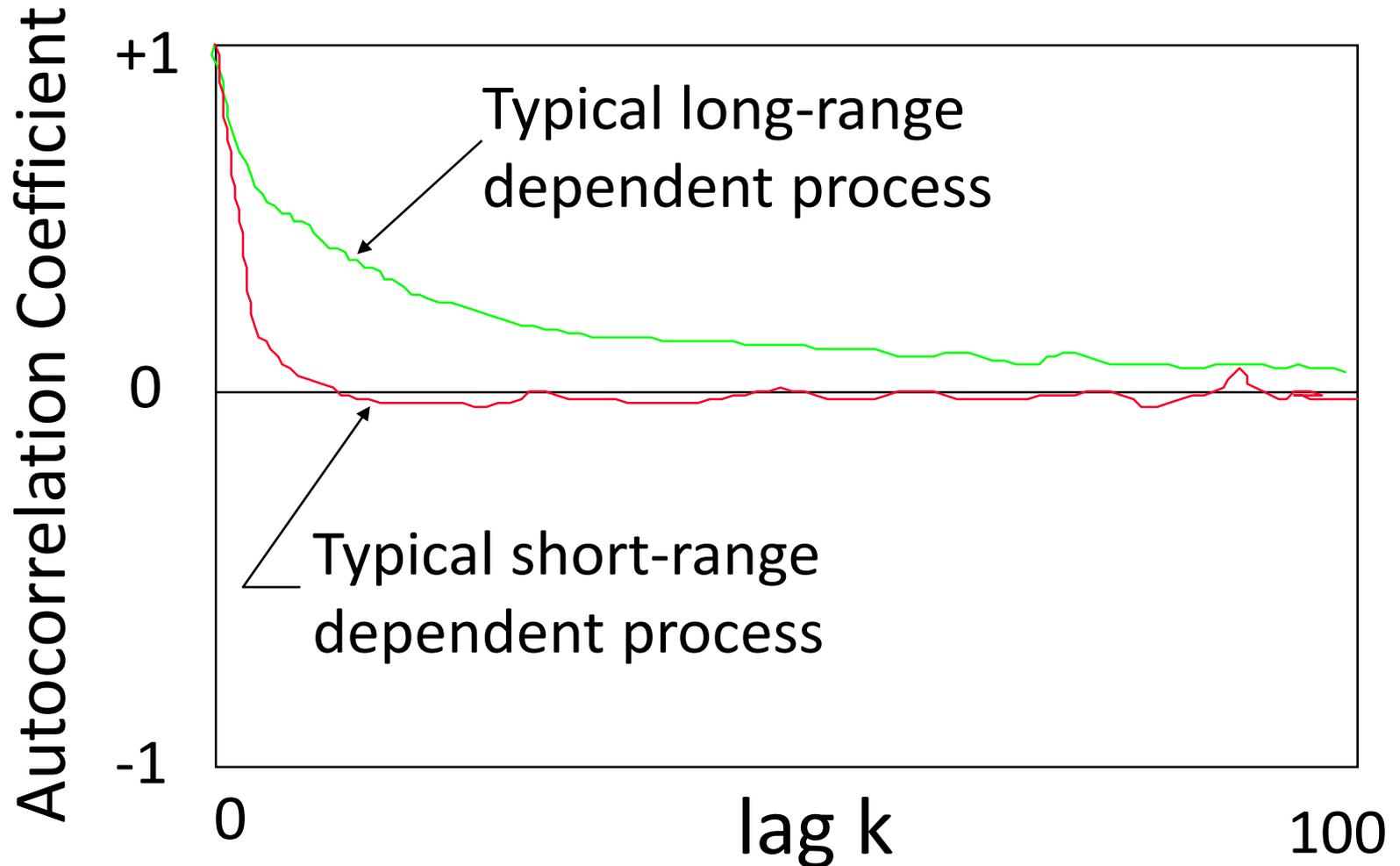




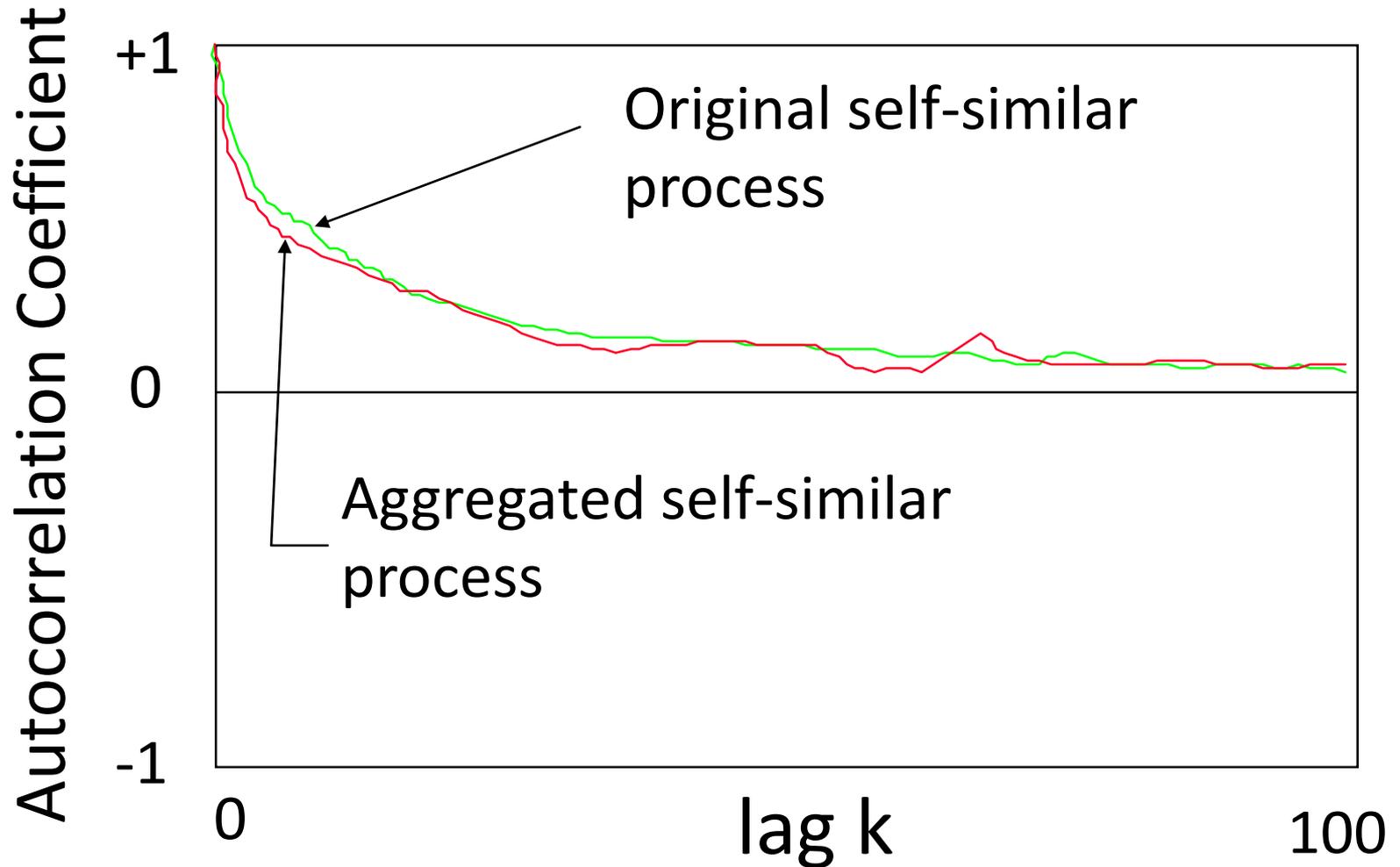




- For most processes (e.g., Poisson, or compound Poisson), the autocorrelation function drops to zero very quickly (usually immediately, or exponentially fast)
- For self-similar processes, the autocorrelation function drops very slowly (i.e., hyperbolically) toward zero, but may never reach zero
- Non-summable autocorrelation function



- For self-similar processes, the autocorrelation function for the aggregated process is indistinguishable from that of the original process
- If autocorrelation coefficients match for all lags k , then called exactly self-similar
- If autocorrelation coefficients match only for large lags k , then called asymptotically self-similar



- Aggregation of a time series $X(t)$ means smoothing the time series by averaging the observations over non-overlapping blocks of size m to get a new time series $X(t)$



- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1...

- Then the aggregated series for $m = 2$ is:

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1...

- Then the aggregated series for $m = 2$ is:

4.5 8.0 2.5 5.0 6.0 7.5 7.0 4.0 4.5 5.0...

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1...

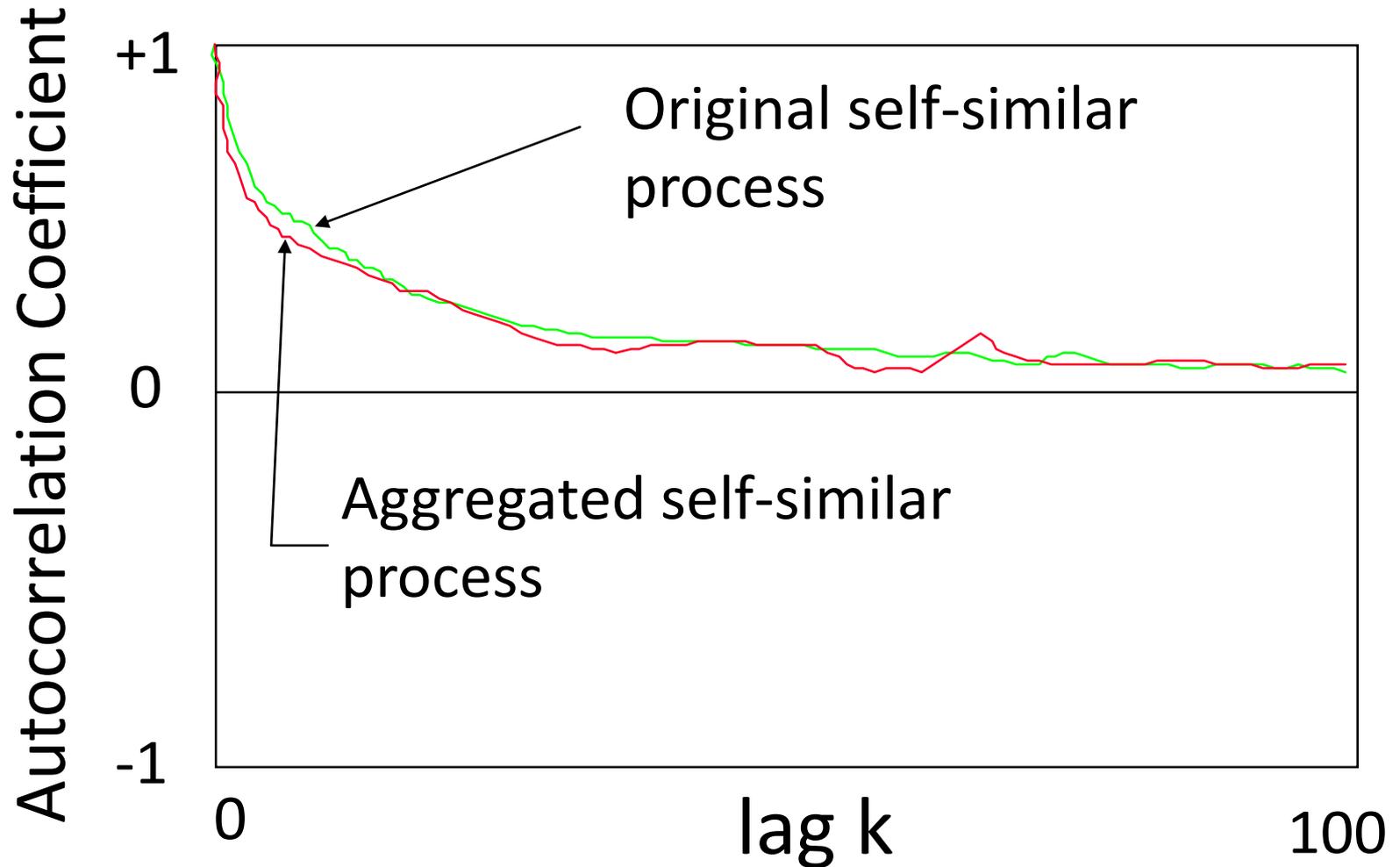
Then the aggregated time series for $m = 5$ is:

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1...

Then the aggregated time series for $m = 5$ is:

6.0 4.4 6.4 4.8 ...



- For almost all naturally occurring time series, the rescaled adjusted range statistic (also called the R/S statistic) for sample size n obeys the relationship

$$E[R(n)/S(n)] = c n^H$$

where:

$$R(n) = \max(0, W_1, \dots, W_n) - \min(0, W_1, \dots, W_n)$$

$S(n)$ is the sample standard deviation, and

$$W_k = \sum_{i=1}^k X_i - k \bar{X}_n \quad \text{for } k = 1, 2, \dots, n$$

- For models with only short range dependence, H is almost always 0.5
- For self-similar processes, $0.5 < H < 1.0$
- This discrepancy is called the Hurst Effect, and H is called the Hurst parameter
- Single parameter to characterize self-similar process!

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1

- There are 20 data points in this example

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1

- There are 20 data points in this example
- For R/S analysis with $n = 1$, you get 20 samples, each of size 1: (boring base case)

Block 1: $\bar{X} = 2$, $W_1 = 0$, $R(n) = 0$, $S(n) = 0$

Block 2: $\bar{X} = 7$, $W_1 = 0$, $R(n) = 0$, $S(n) = 0$

Block 3: $\bar{X} = 4$, $W_1 = 0$, $R(n) = 0$, $S(n) = 0$

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1

- For R/S analysis with $n = 2$, you get 10 samples, each of size 2:

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1

- For R/S analysis with $n = 2$, you get 10 samples, each of size 2:

Block 1: $\bar{X}_n = 4.5$, $W_1 = -2.5$, $W_2 = 0$,

$R(n) = 0 - (-2.5) = 2.5$, $S(n) = 2.5$,

$R(n)/S(n) = 1.0$

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1

- For R/S analysis with $n = 2$, you get 10 samples, each of size 2:

Block 2: $\bar{X}_n = 8.0$, $W_1 = -4.0$, $W_2 = 0$,

$R(n) = 0 - (-4.0) = 4.0$, $S(n) = 4.0$,

$R(n)/S(n) = 1.0$

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1

- For R/S analysis with $n = 5$, you get 4 samples, each of size 5:

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1

- For R/S analysis with $n = 5$, you get 4 samples, each of size 4:

Block 1: $\bar{X}_n = 6.0$, $W_1 = -4.0$, $W_2 = -3.0$,

$W_3 = -5.0$, $W_4 = 1.0$, $W_5 = 0$, $S(n) = 3.41$,

$R(n) = 1.0 - (-5.0) = 6.0$, $R(n)/S(n) = 1.76$

- Suppose the original time series $X(t)$ contains the following (made up) values:

2 7 4 12 5 0 8 2 8 4 6 9 11 3 3 5 7 2 9 1

- For R/S analysis with $n = 5$, you get 4 samples, each of size 4:

Block 2: $\bar{X}_n = 4.4$, $W_1 = -4.4$, $W_2 = -0.8$,

$W_3 = -3.2$, $W_4 = 0.4$, $W_5 = 0$, $S(n) = 3.2$,

$R(n) = 0.4 - (-4.4) = 4.8$, $R(n)/S(n) = 1.5$

- Another way of testing for self-similarity, and estimating the Hurst parameter
- Plot the R/S statistic for different values of n , with a log scale on each axis
- If time series is self-similar, the resulting plot will have a straight line shape with a slope H that is greater than 0.5
- Called an R/S plot, or R/S pox diagram

R/S Statistic



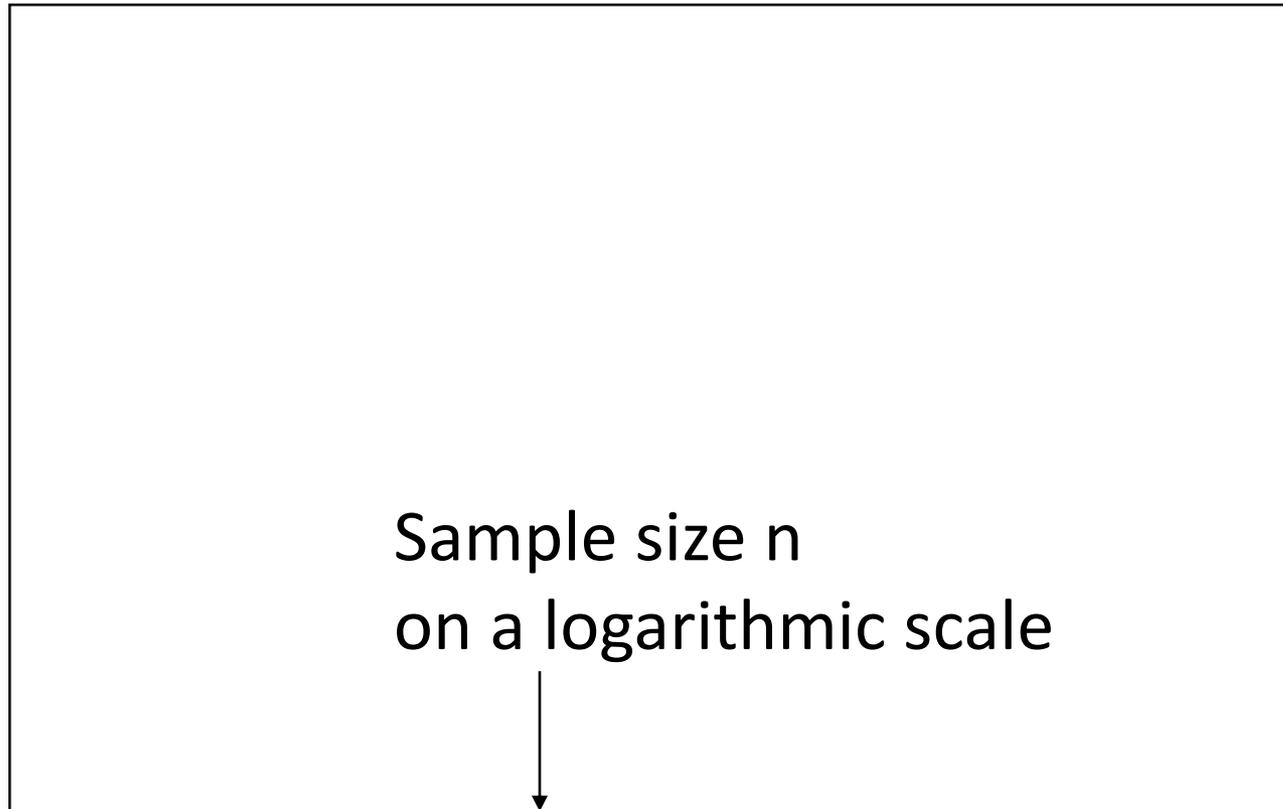
Block Size n

R/S Statistic

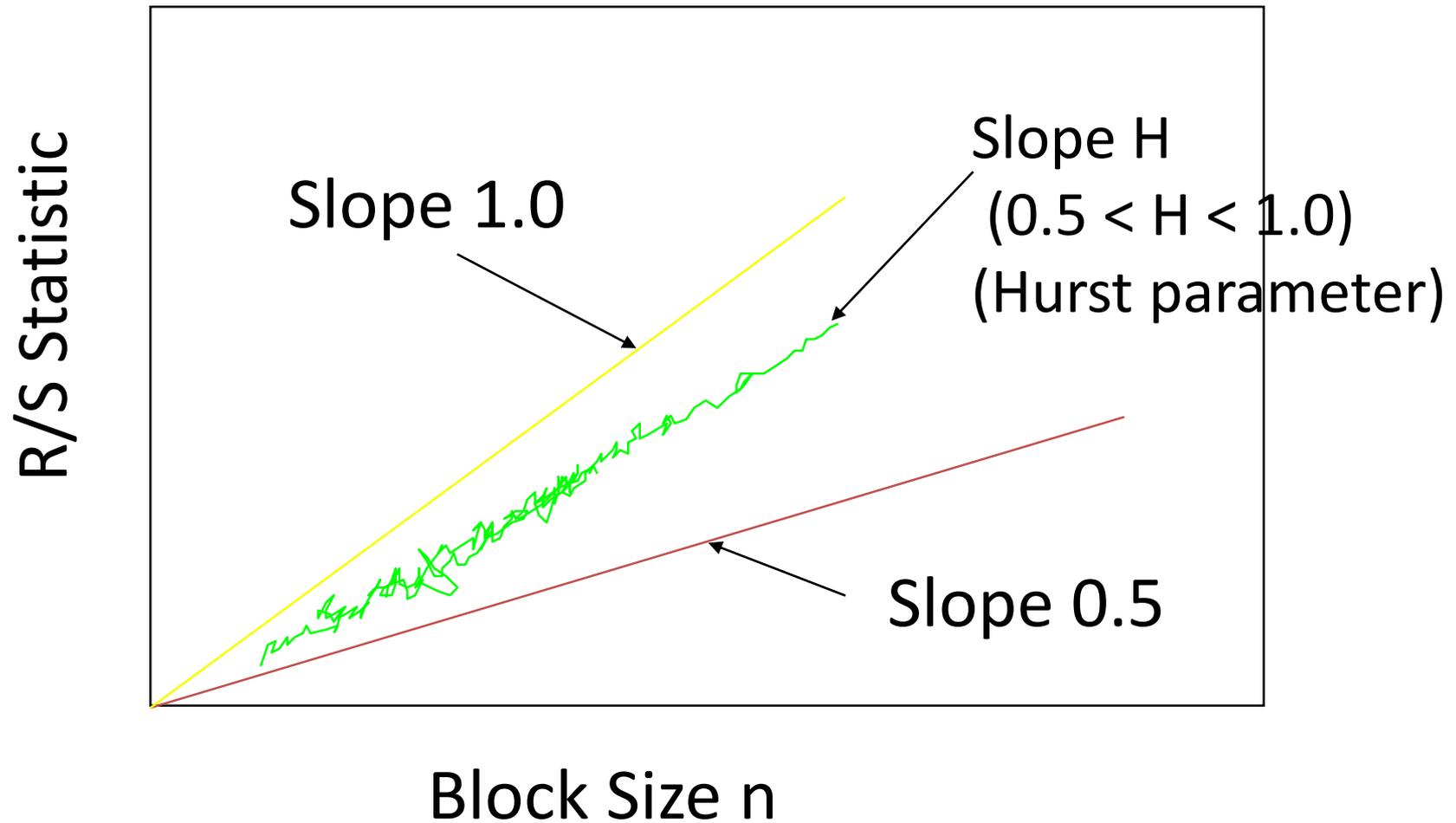
R/S statistic $R(n)/S(n)$
on a logarithmic scale

Block Size n

R/S Statistic



Block Size n



- Self-similarity is an important mathematical property that has been identified as present in network traffic measurements
- Important property: burstiness across many time scales, traffic does not aggregate well
- There exist several mathematical methods to test for the presence of self-similarity, and to estimate the Hurst parameter H
- There exist models for self-similar traffic