Assignments:

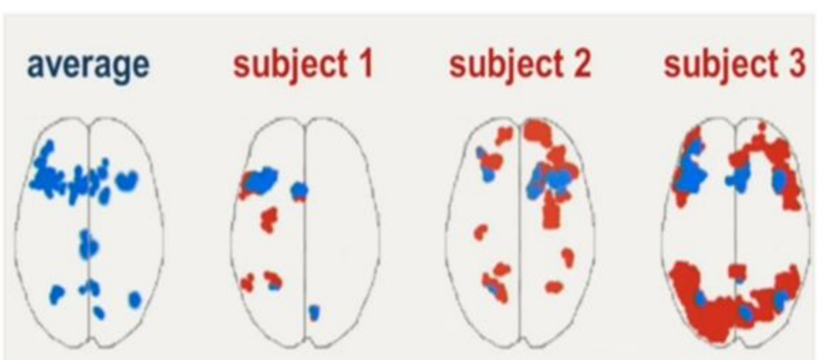
Basic TSA
Basic NLTSA

End of Average

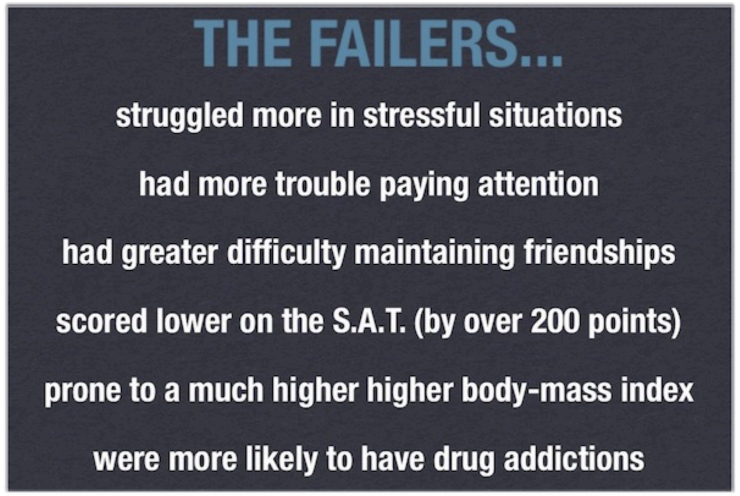
Story so far …

- *Background:* Complexity Science / **Science of the Individual** / Systems Biology
- **Idiographic** versus **Nomothetic** goal of scientific explanation

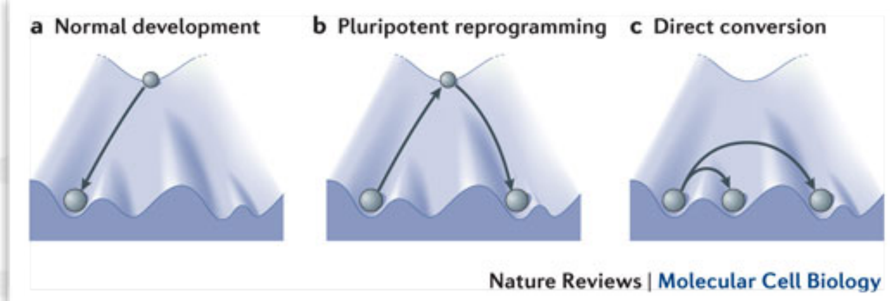
Principle of jaggedness
no individual corresponds to average

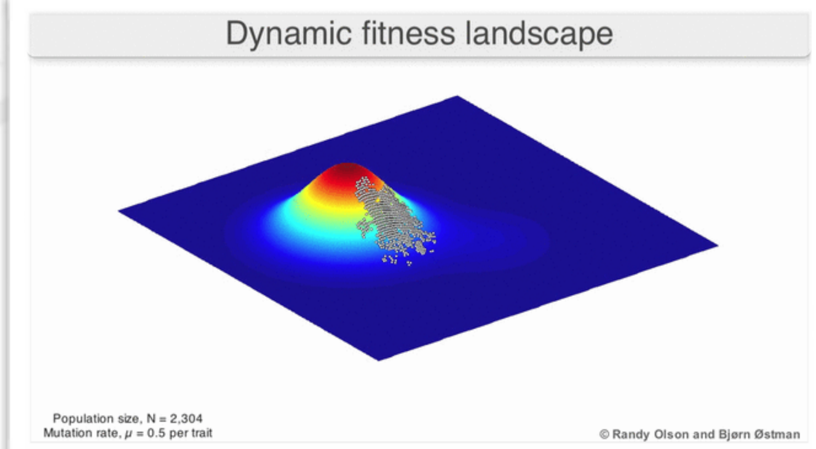


Principle of context
no behaviour is context independent



Principle of pathways
multiple trajectories to 'success'





Thread 1:

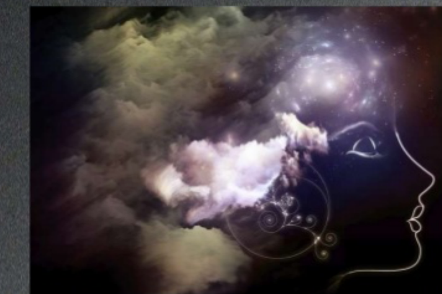
At age 27-32, those who had waited longest during the Marshmallow Test in preschool had a lower BMI, a better sense of self-worth, pursued their goals more effectively, and coped better with stress and frustration.

(pg. 5)

long range correlations
attractor / repellor
resistance to change
context sensitivity

Thread 2:

Resisting temptation is difficult because the brain's "hot system" is heavily biased towards the present: it takes full account of immediate rewards, but discounts rewards that are delayed.



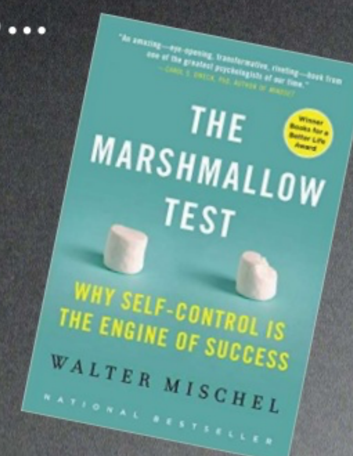
(pg. 255)

Thread 6:

The more we learn about nature and nurture, the more it is clear that they inseparably shape each other. "A predisposition does not a pre- determination make."

(pg. 91-93)

Teasing 10 threads from Walter Mischel's…



Thread 4:

Prolonged stress impairs the prefrontal cortex, essential for things like surviving high school, holding down a job, avoiding depression and refraining from decisions that seem intuitively right but turn out to be really stupid.

(pg. 49)

Thread 7:

Each child who waited successfully had a distinctive methodology for self-control. First, they had to remember and actively keep in mind their chosen goal.

(pg. 107)

complex dynamics
different paths
(multi-realisability)

metaphors from thermodynamics

Thread 10:

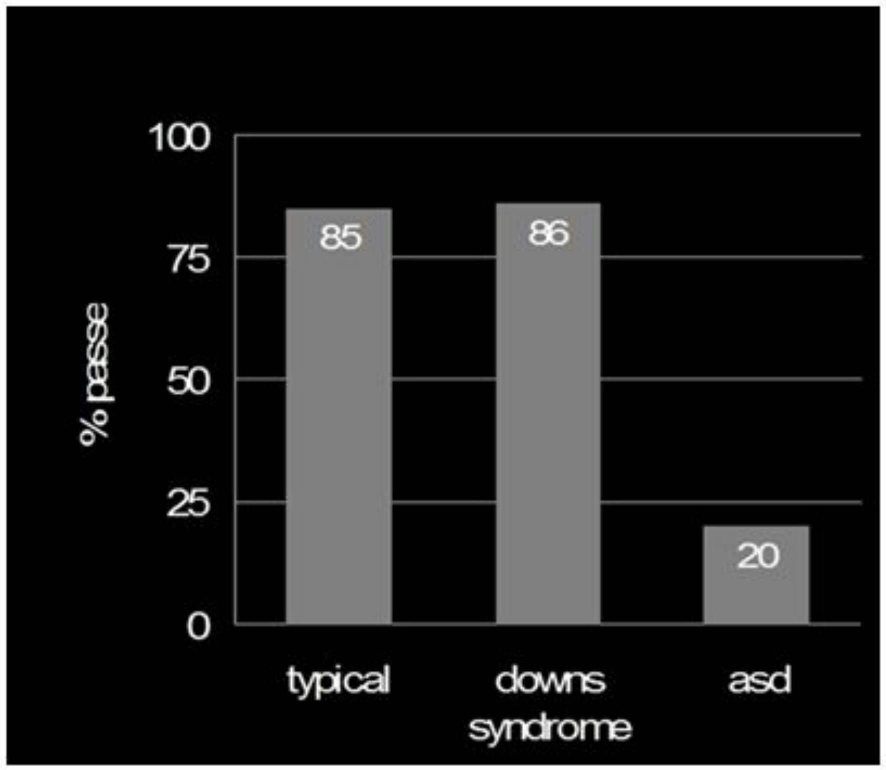
The Fundamental Marshmallow Principle: "Cool the now; heat the later!"

(pg. 256)

only four of the 20 autistic children (20%) answered correctly

theory of mind?

Sally-Anne problem

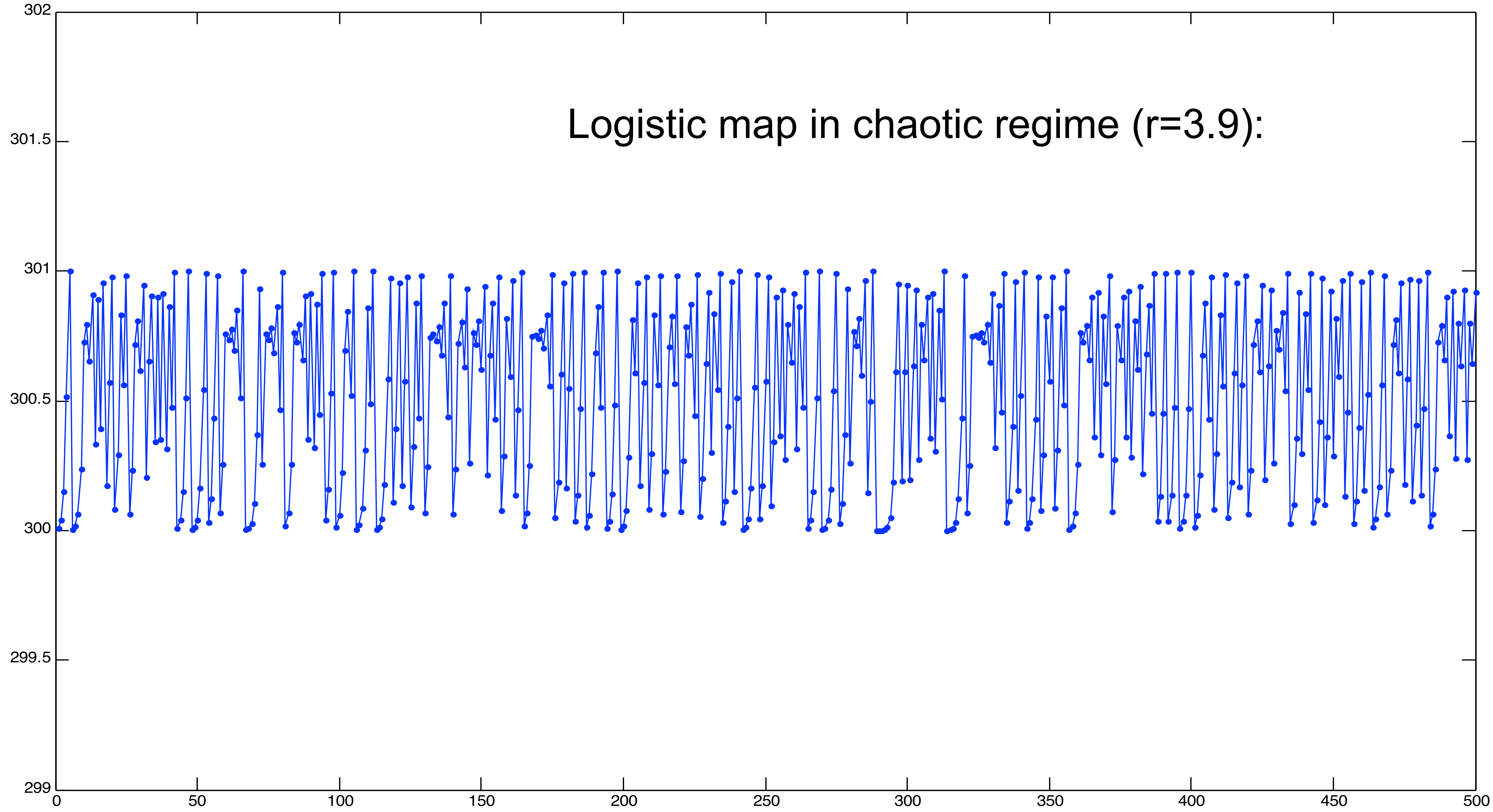


Baron-Cohen, Leslie, and Frith (1985)
Social and emotional problems secondary to cognitive problem

Instruct to keep the chocolate…. no problem!

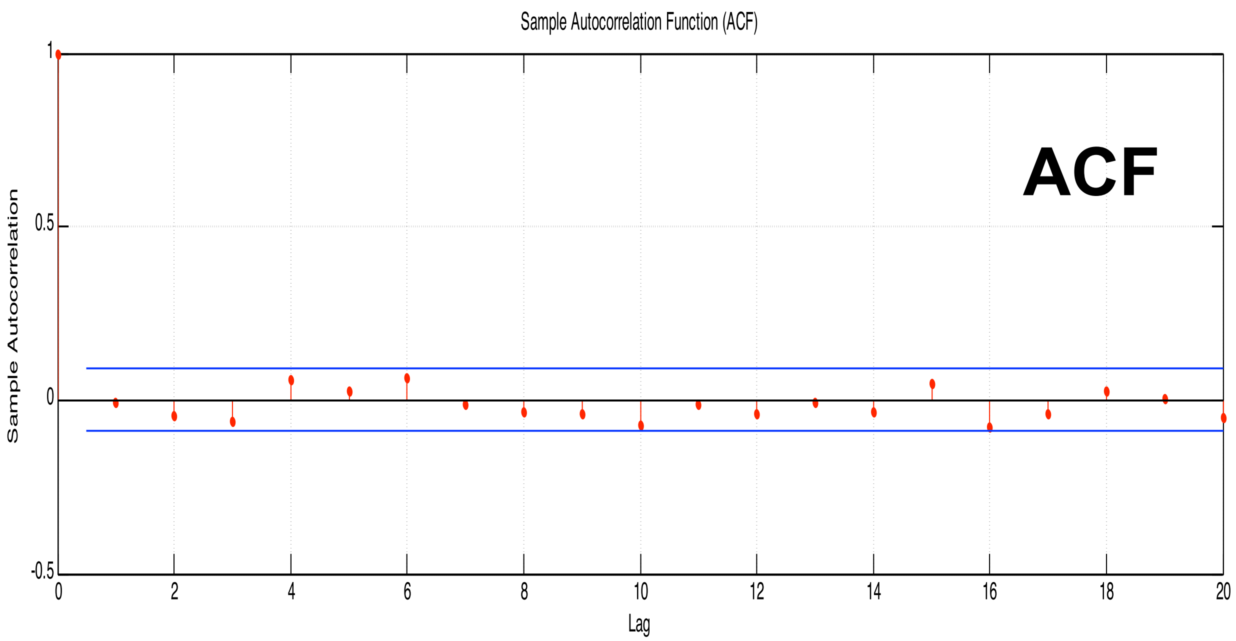
Problems with linear methods (data assumptions)

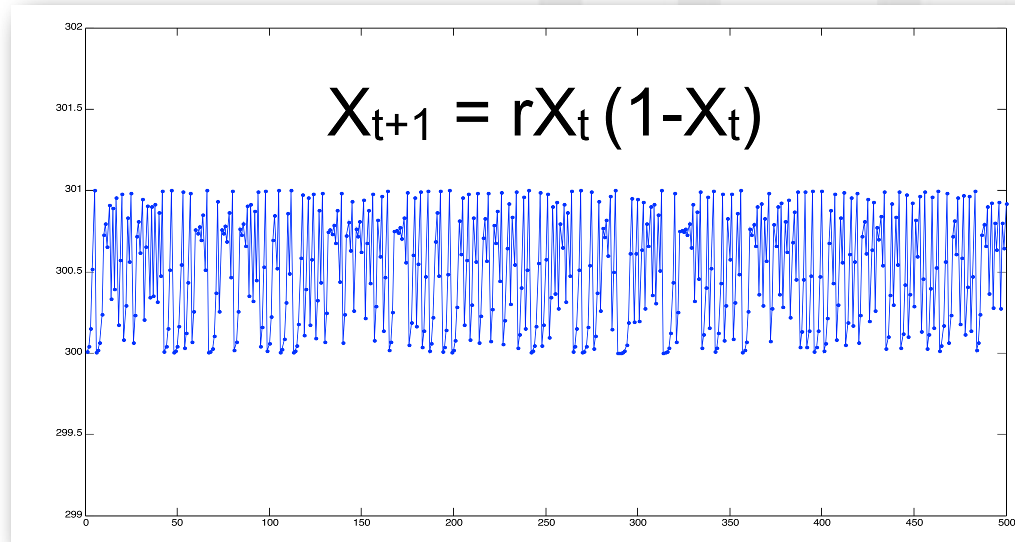
And what about deterministic CHAOS?



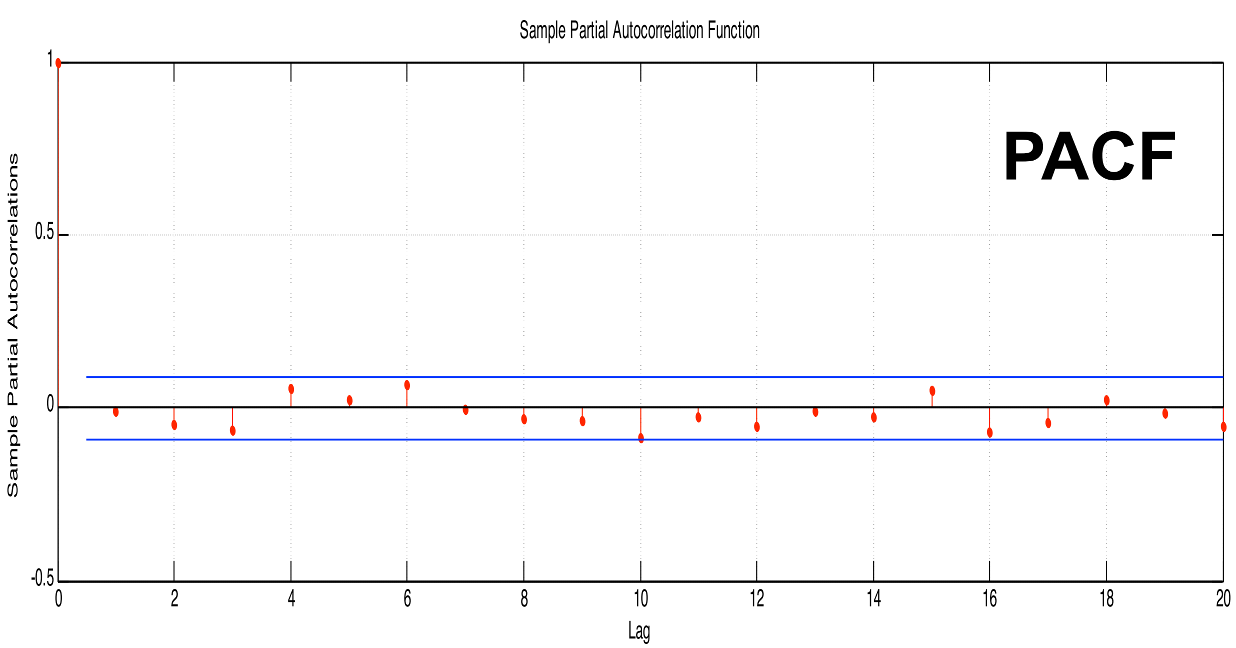
Problems w/ linear methods

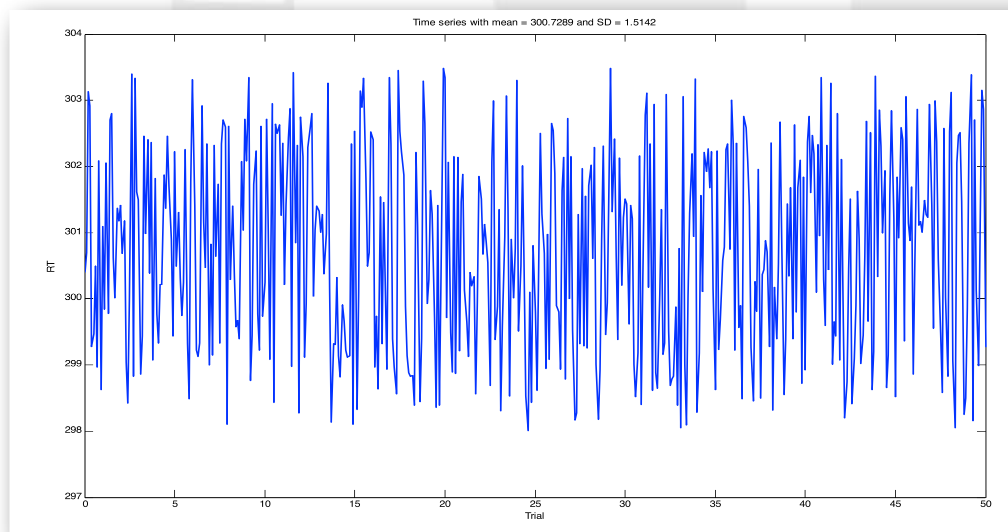
??? - A Random Process ??? - But we know the equation !!!!



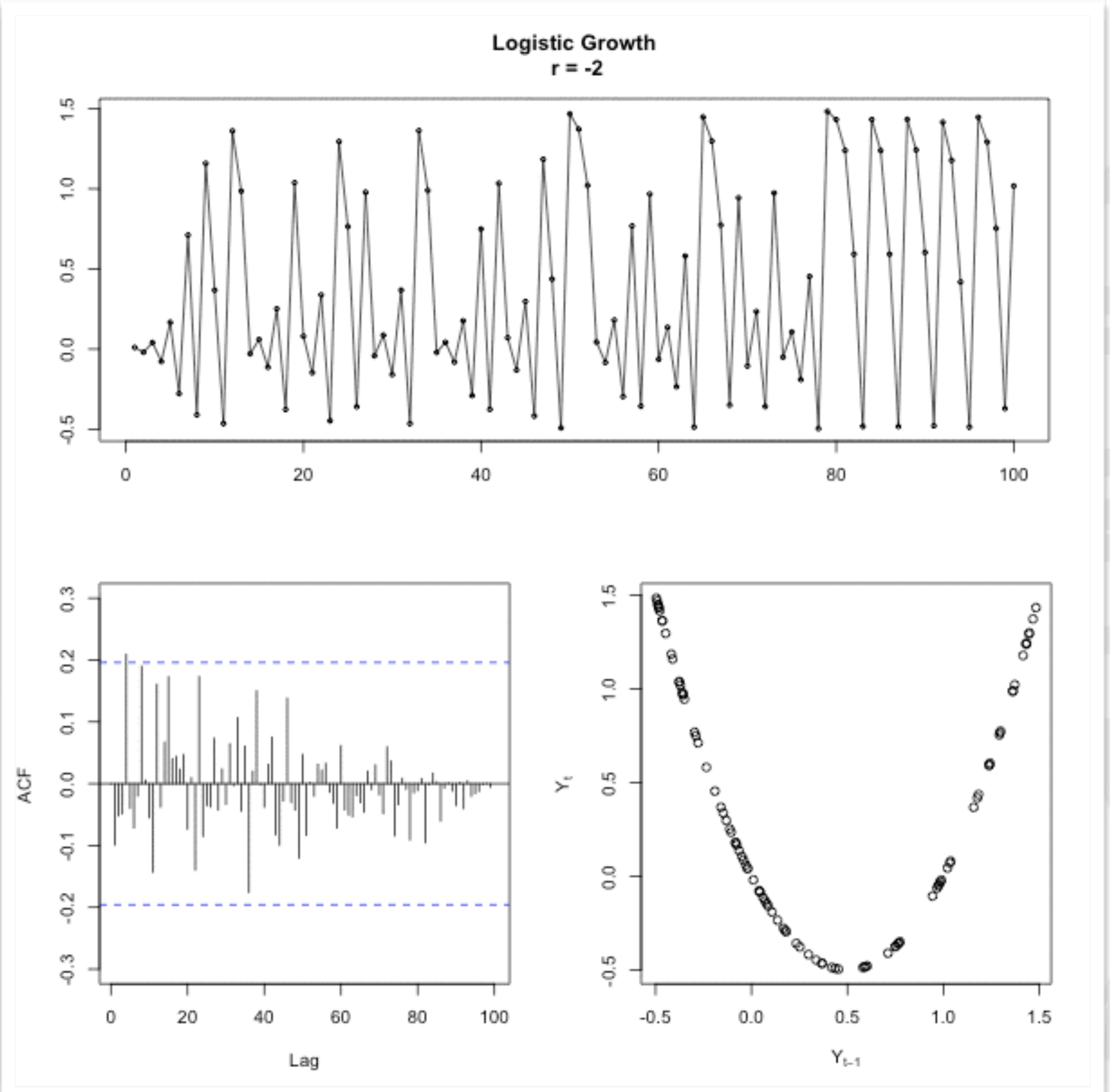


?





"Things that look random, but are not" (Lorenz, 1972)



Logistic Growth
r = -2
ACF
Lag
Y_t
Y_{t-1}

Rank Version of von Neumann's Ratio Test for Randomness

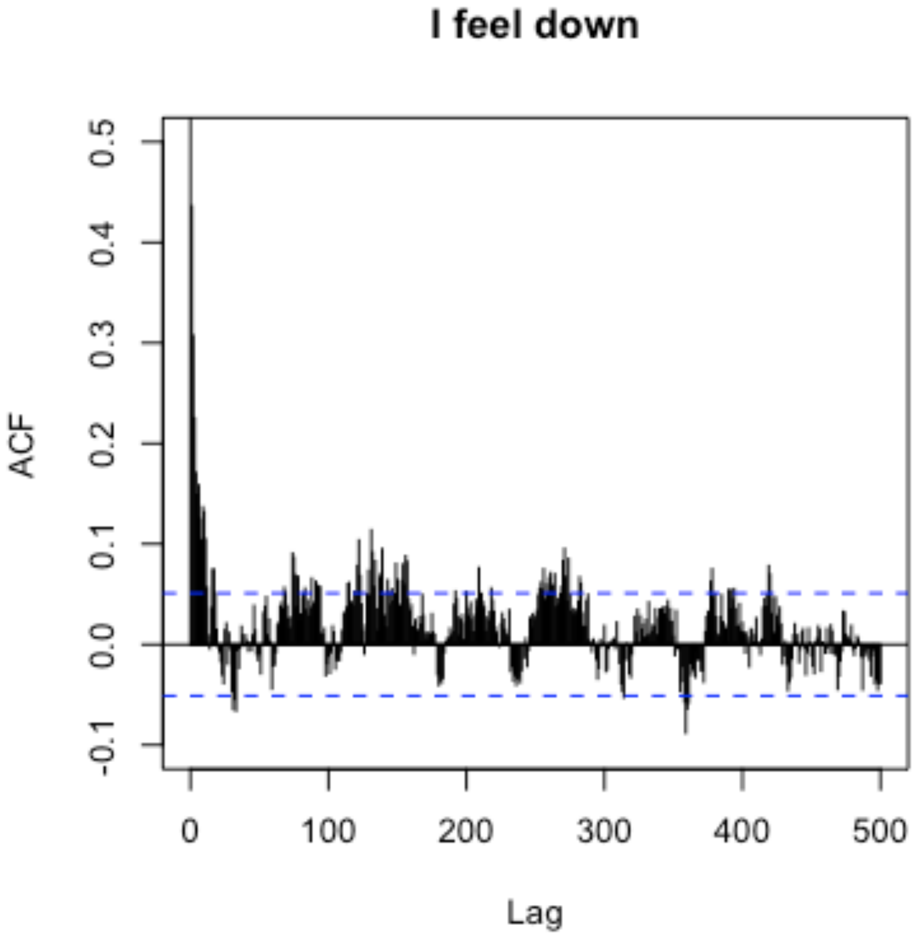
Kwiatkowski–Phillips–Schmidt–Shin (KPSS)

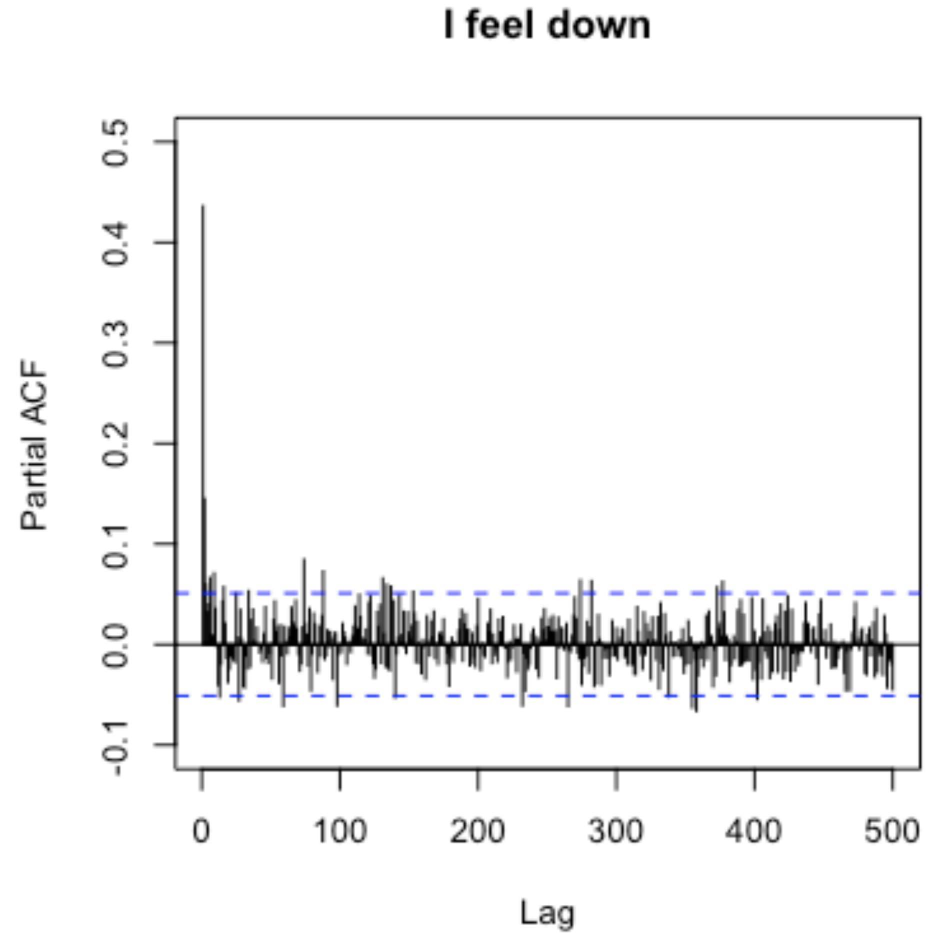
	Bartels rank test H0 = Random H1 = Non-random		**KPSS test H0 = Level Stationary H1 = Unit root**		**KPSS test H0 = Trend Stationary H1 = Unit root**		**Significant partial autocorrelations**	
Item	*All data*	*Subset*	*All data*	*Subset*	*All data*	*Subset*	*Lag 2-99*	*Lag 100-1000*
I feel relaxed	<.001*	<.001*	0.092	0.046	0.036	0.021	2	6
I feel down	<.001*	<.001*	<.010*	0.100	0.100	0.100	8	8
I feel irritated	<.001*	<.001*	<.010*	0.052	<.010*	0.100	5	7
I feel satisfied	<.001*	<.001*	0.100	0.019	0.100	0.098	2	4
I feel lonely	<.001*	<.001*	<.010*	0.100	0.100	0.100	5	9
I feel anxious	<.001*	<.001*	<.010*	0.100	0.100	0.100	8	11
I feel enthusiastic	<.001*	<.001*	0.100	0.100	0.100	0.100	4	6
I feel suspicious	<.001*	<.001*	<.010*	0.061	0.041	0.027	9	9
I feel cheerful	<.001*	<.001*	0.100	0.059	0.100	0.046	4	6
I feel guilty	<.001*	<.001*	<.010*	<.010*	0.094	0.100	7	7
I feel indecisive	<.001*	<.001*	0.100	<.010*	0.050	0.100	7	7
I feel strong	<.001*	<.001*	0.100	0.021	0.100	0.100	6	6
I feel restless	<.001*	<.001*	<.010*	0.070	<.010*	0.075	11	4
I feel agitated	<.001*	<.001*	<.010*	0.100	<.010*	0.100	6	5
I worry	<.001*	<.001*	<.010*	0.100	0.100	0.100	10	11
I can concentrate well	<.001*	<.001*	<.010*	<.010*	0.100	0.100	4	8
I like myself	<.001*	<.001*	0.100	<.010*	0.082	0.100	5	5
I am ashamed of myself	<.001*	<.001*	<.010*	0.100	0.100	0.100	8	6
I doubt myself	<.001*	<.001*	0.048	0.100	0.093	0.100	7	5
I can handle anything	<.001*	<.001*	0.055	0.047	0.100	0.100	4	8
I am hungry	0.068	0.068	<.010*	0.020	<.010*	0.049	6	2
I am tired	<.001*	<.001*	<.010*	0.100	0.079	0.978	11	5
I am in pain	<.001*	<.001*	0.100	0.024	<.010*	0.100	4	2
I feel dizzy	0.854		<.010*		0.050		6	7
I have a dry mouth	0.958		0.029		0.042		1	8
I feel nauseous	0.854		0.100		0.100		4	9
I have a headache	<.001*	0.8544	0.018	0.020	<.010*	0.100	7	4
I am sleepy	<.001*	0.958	<.010*	0.011	<.010*	0.100	7	4
From the last beep onwards I was physically active	<.001*	0.854	<.010*	0.100	<.010*	0.100	3	3
Sum of significant tests (%)	25 (86%)	22 (85%)	16 (55%)	4 (15%)	8 (28%)	0 (0%)		

Note.

N = 1476 for all data. N = 292 for the subset **[= START ACTUAL REDUCTION]**.

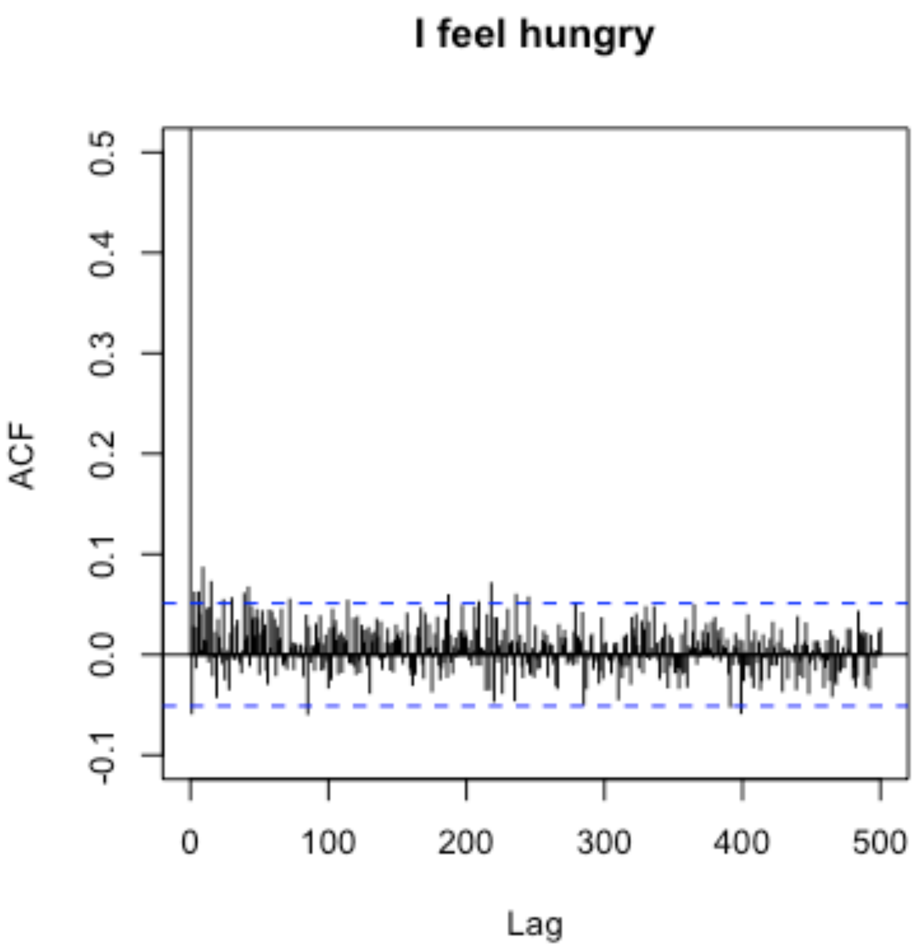
* indicates statistically significant test statistics. For Bartels rank test, results were considered significant for $p<.002$. The KPSS test only provides p-values in between .01 and .10. For the KPSS test, $p<.010$ was considered significant. Three items showed no variance during the baseline period included in the subset and were therefore omitted from analysis of the subset.

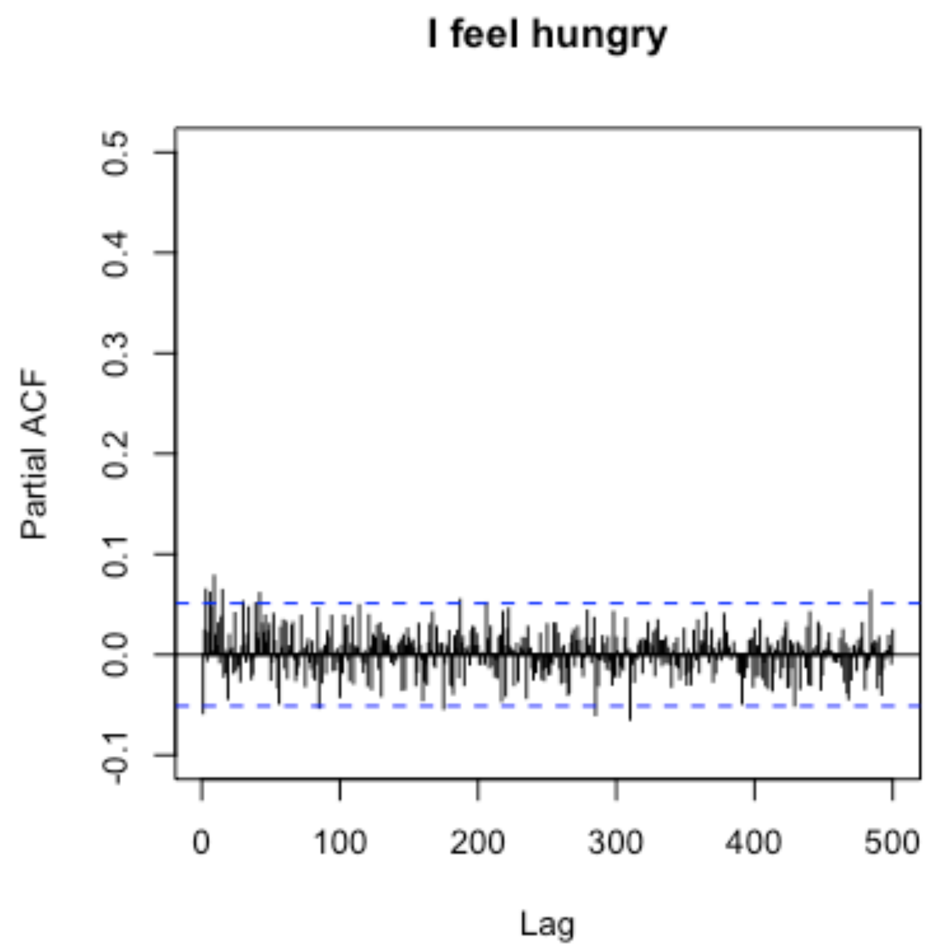




Questions abt. *mental internal states* like ***mood*** resemble non-ergodic processes:

- long memory
- non-stationary
- non-homogeneous
- non-stationary ACF





Questions abt. *physical internal states* like ***hunger*** resemble ergodic processes:

- no long memory
- stationary
- homogeneous
- stationary ACF

Dynamics of Complex Systems

Scaling

Fractal Geometry

Fluctuation Analysis

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Scaling phenomena

How long is the coast of Great-Britain?

Scaling phenomena

scale
11.5 x 200 = 2300 km

scale
28 x 100 = 2800 km

scale
70 x 50 = 3500 km

Length <u>systematically</u> depends on the size of the measurement stick you use!

https://en.wikipedia.org/wiki/Fractal_dimension

Scaling phenomena

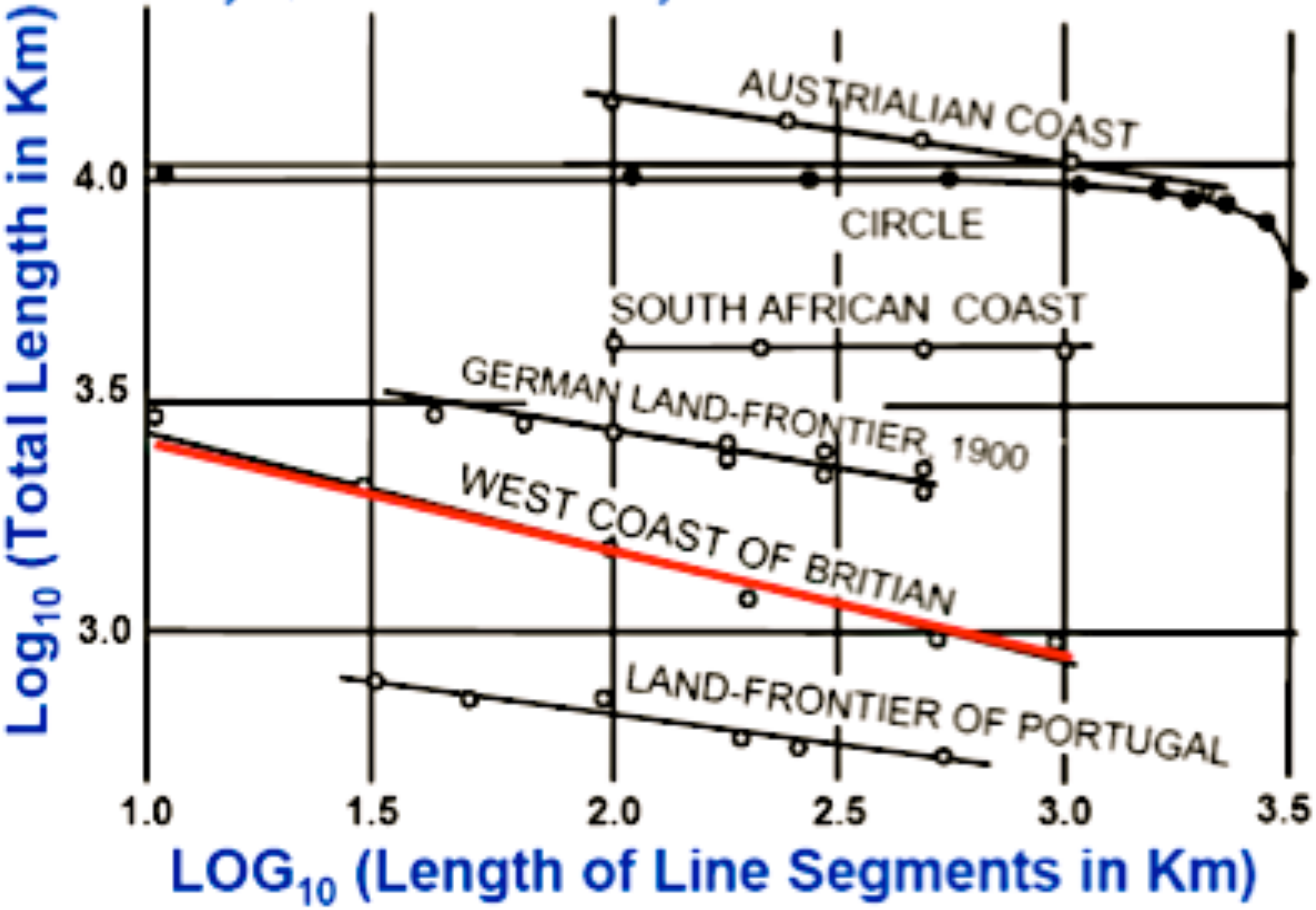
"scaling of bulk with size"
(Theiler, 1990)

The formal answer to the question is:
"There is no characteristic scale at which the length of the coast of GB can be expressed"

Mandelbrot, B. B. (1967). How long is the coast of Britain? Statistical self-similarity and fractional dimension. *Science, 156*(3775), 636–8.

How Long is the Coastline of Britain?

Richardson 1961 The problem of contiguity: An Appendix to Statistics of Deadly Quarrels General Systems Yearbook 6:139-187



Scale invariance…

no meaningful central moments can be defined

Mean and SD characterise the data only relative to the scale of observation (e.g. sample size)

A *power law* scaling relation (**LOG scale**):
There is no characteristic length, just an indication of complexity

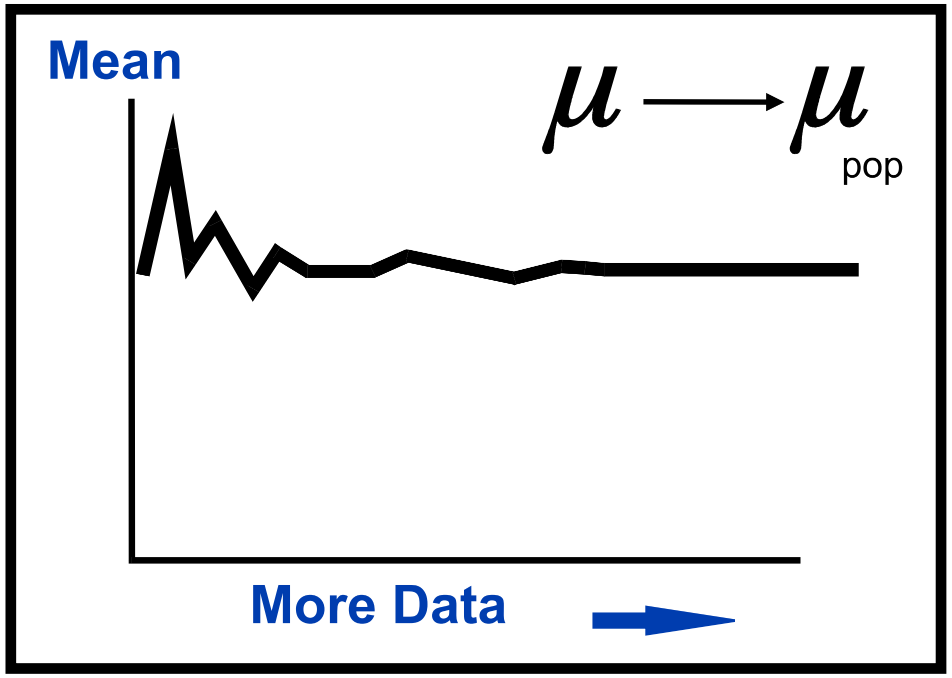
Scaling phenomena

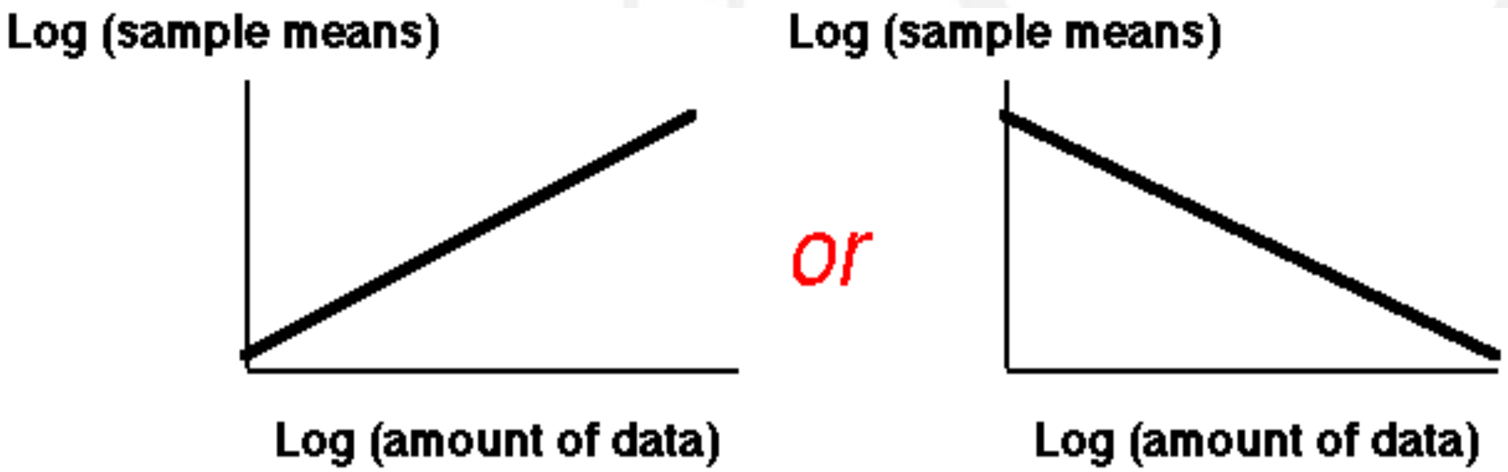
Independent observations of random variables

μ±σ are sufficient to characterise absence of dependencies in the data:
e.g. Expected value of **μ** for **N** = 100, given **σ**

Interdependent observations across different scales

μ±σ are insufficient to characterise dependencies in the data:
e.g. Sample estimates of **μ** change with **N**





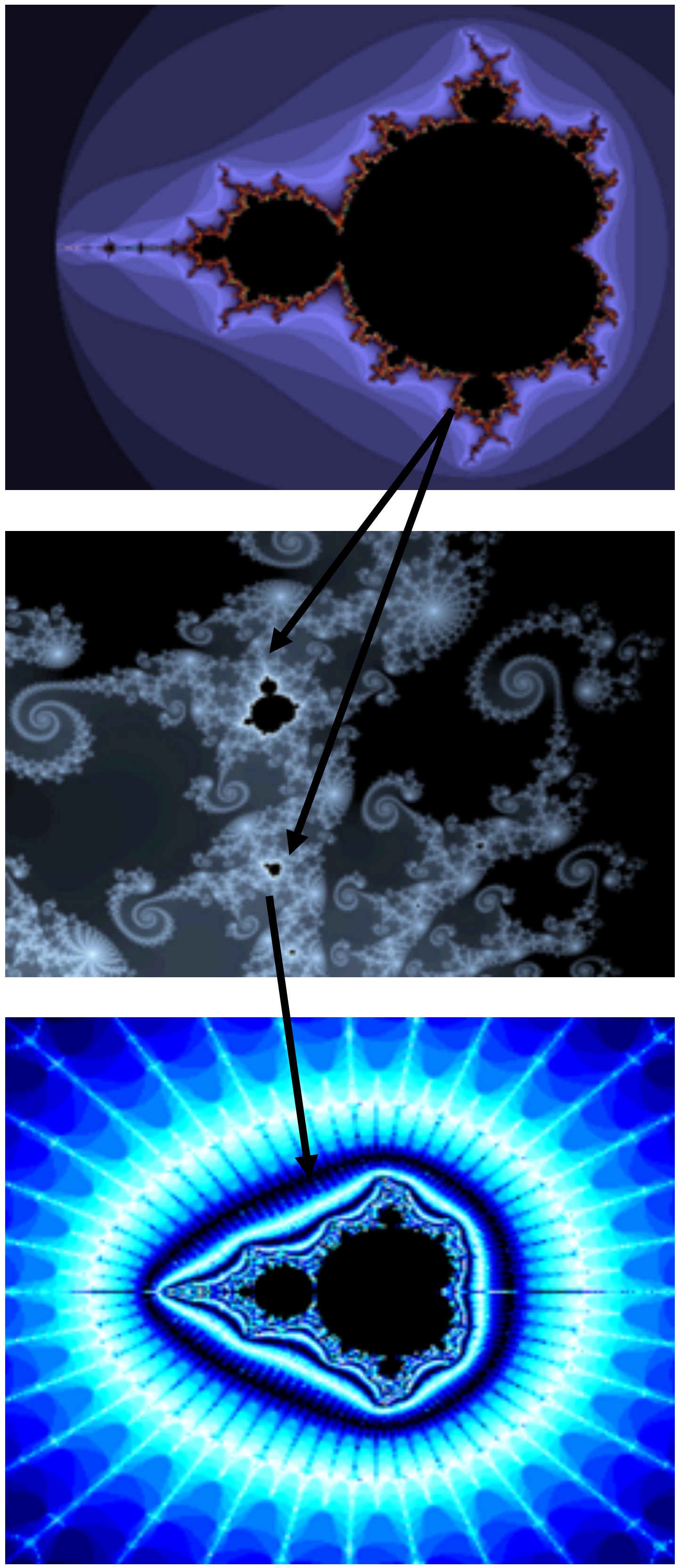
Help! How can I do science without **μ** or **σ**?

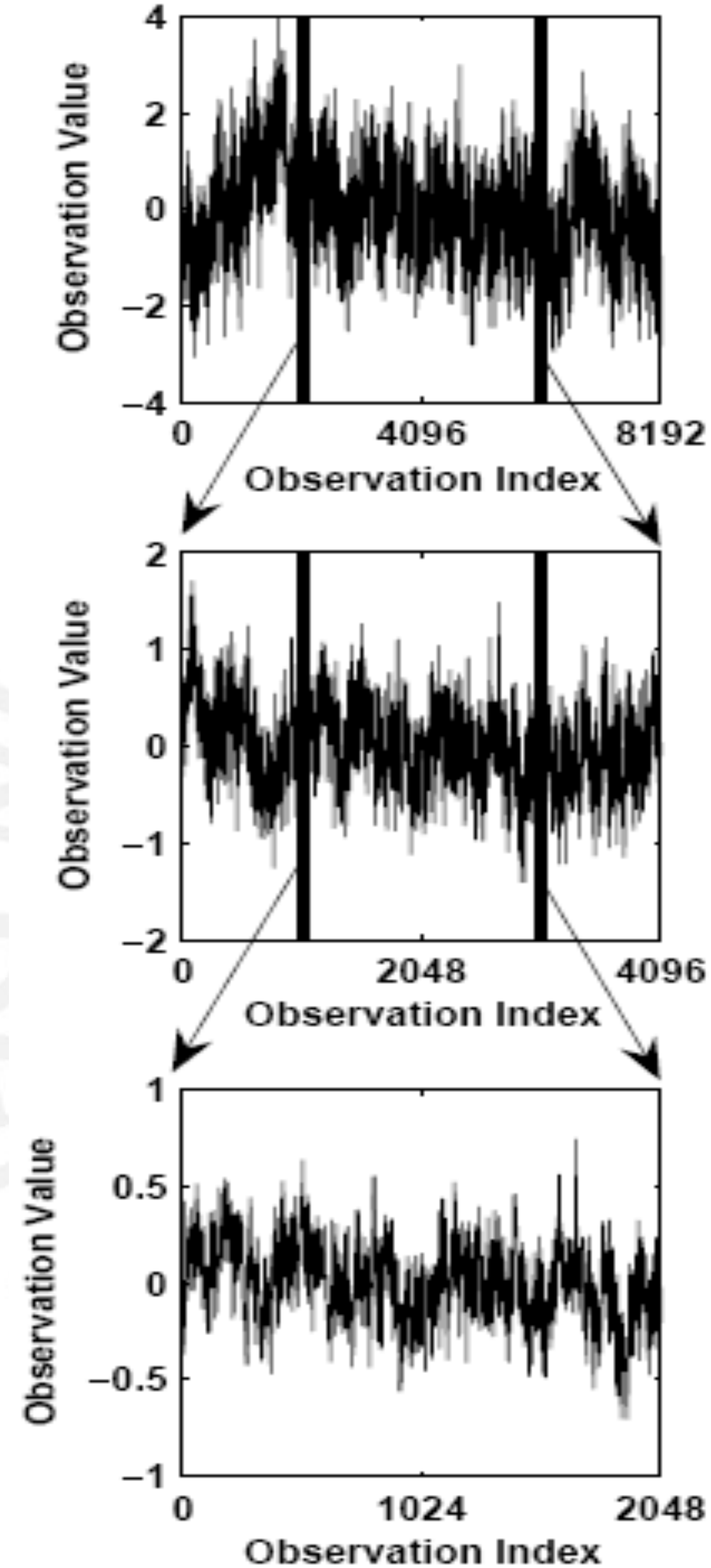
What is scaling?
Self-similarity and Self-affinity

Object looks roughly the same on all scales = (Statistical) **self-similarity** (“zoom similarity”)

(Statistical) self-similarity is observed after affine transformation = **self-affinity** (“warp similarity”)

Degree of invariance across scales = Dependencies/regularities/correlations across scales





aka: “Fractal scaling”

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Learning & Plasticity
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Scaling phenomena

Scaling relations can emerge with all kinds of observables
They inform about properties of the process / system under scrutiny

Earthquakes (Richter-Law)

frequency of occurrence ~ magnitude

Distribution of mass in the Universe

resolution ~ density

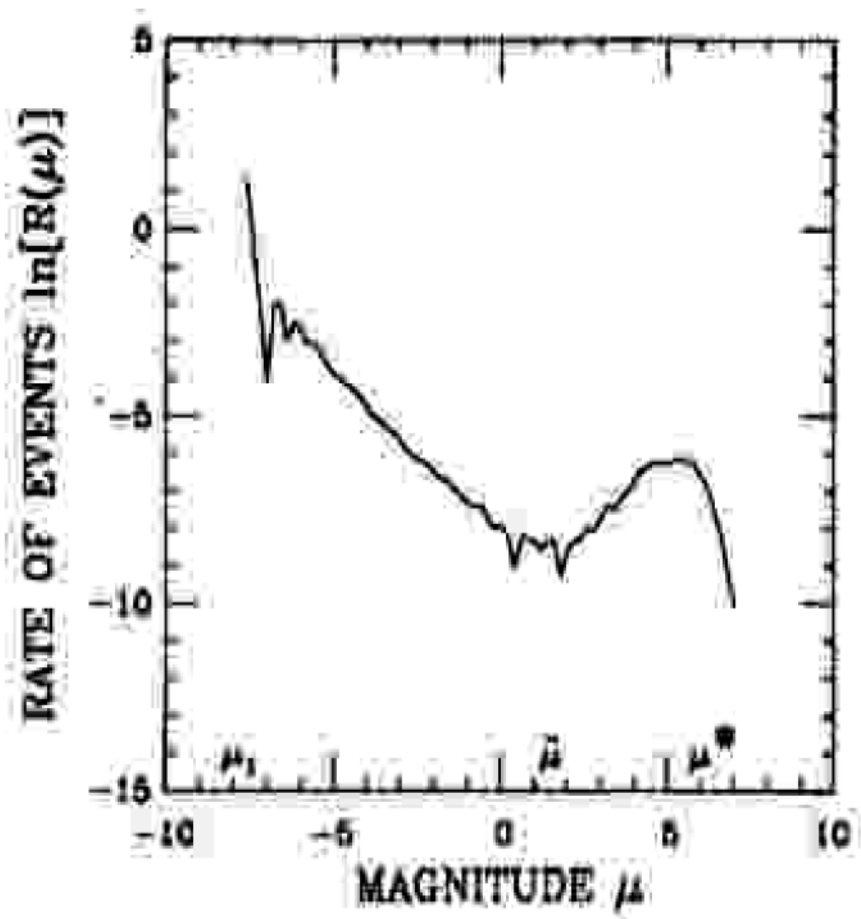
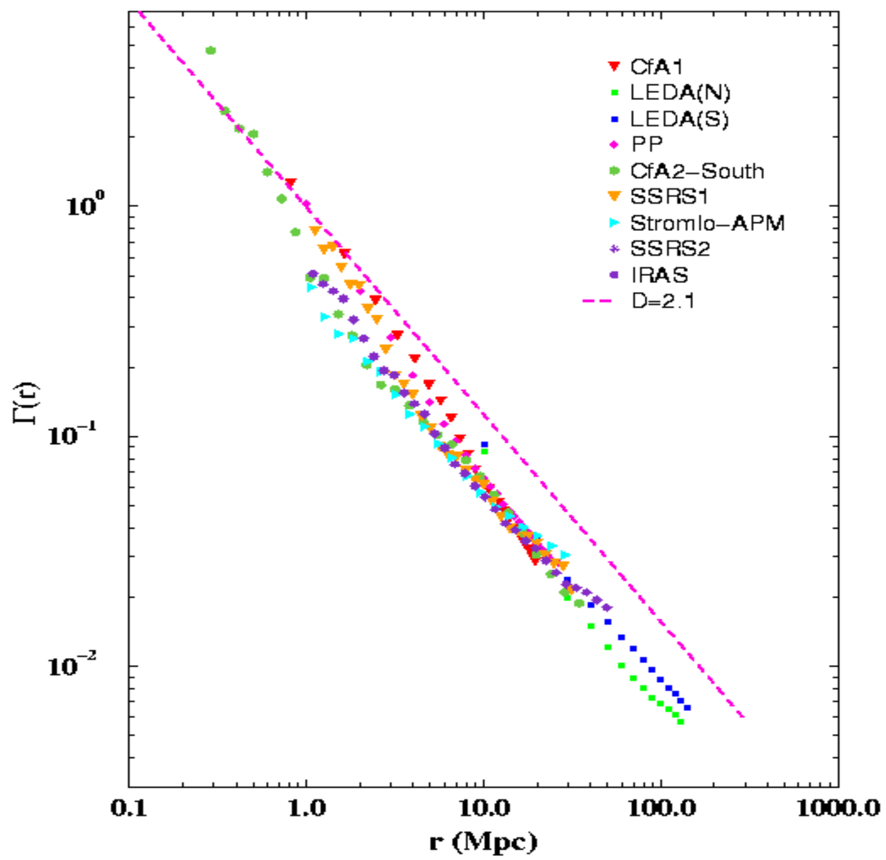


Figure 13: frequency distribution of the slip events (earthquakes) of magnitude μ taken from [53]. Notice the large bump that corresponds to an excess of events of high magnitude.



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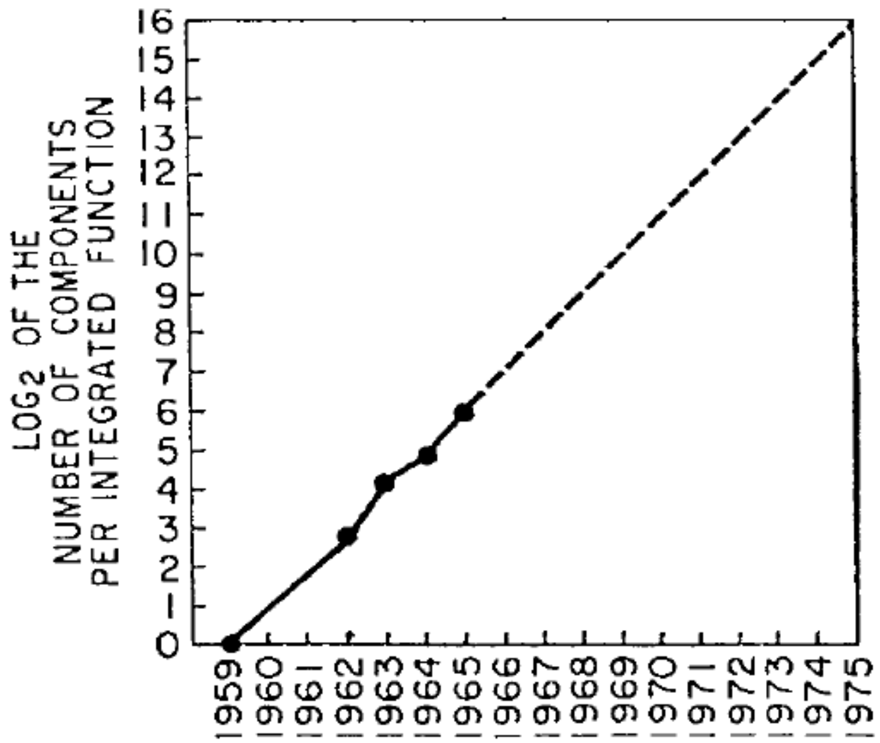
Scaling & Growth

Moore's Law:

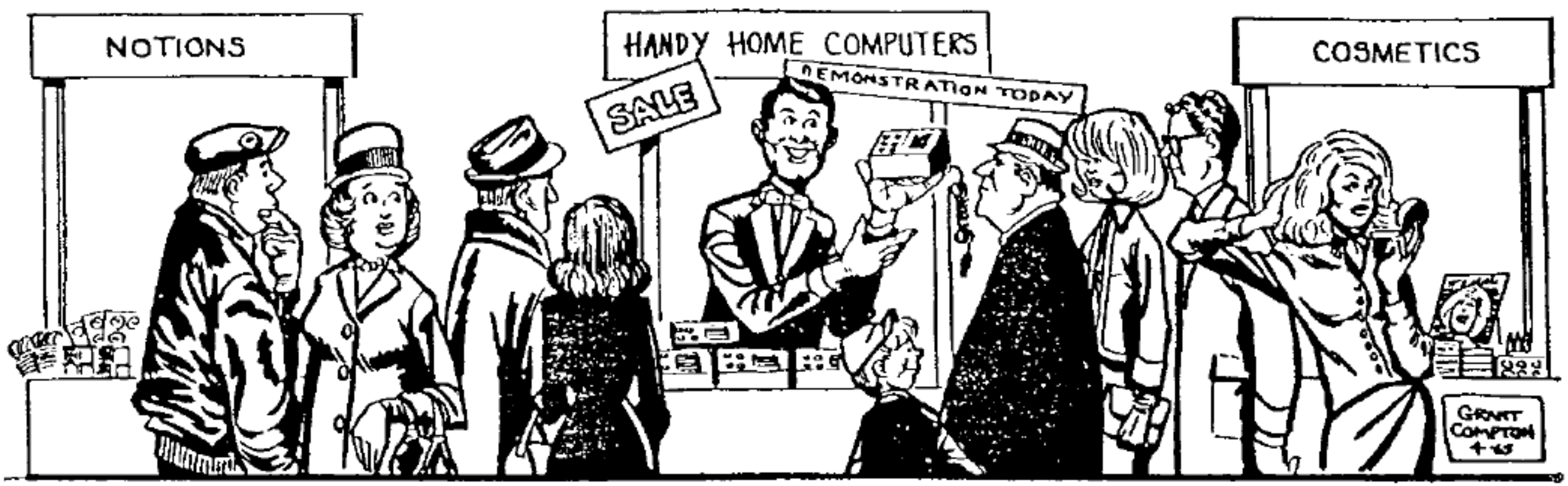
Predicted if speed of innovations in "cramming more components onto integrated circuits" kept up …



Moore's Law:

… we would soon be buying computers at the local market …

which apparently was a preposterous idea



Moore, Gordon E. (1965). "Cramming more components onto integrated circuits"

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Scaling phenomena

Measuring dimension

What is the dimension of these objects?:

Definition (Euclidian) dimension: *The number of degrees of freedom you have to move through a space.*

Definition of a space: *a collection of points*

0 **1** **2** **3**

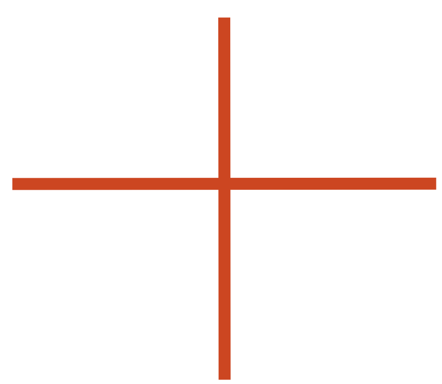
Scaling phenomena

Measuring dimension

What is the dimension of these objects?:

Definition (Euclidian) dimension: *The number of degrees of freedom you have to move through a space.*

Definition of a space: *a collection of points*



Locally 1 dimensional
On the cross-section 2 dimensional

Which one is it, the smallest?

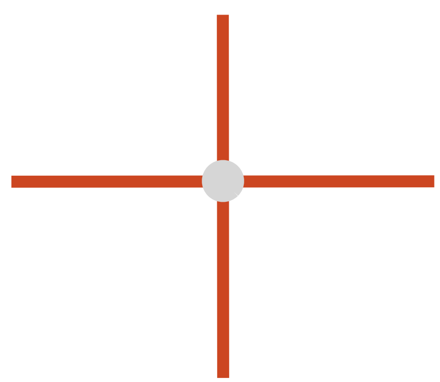
Then this space would be 0 dimensionaal,
because a point = 0

Scaling phenomena

Measuring dimension

Topological Dimension

Introduces *local* and *global* dimension.
Global: Take the dimension of the object with which you can divide the space in two parts and add one.
Constraint: **The dimension must stay the same over linear transformations**



Point = 0 (+ 1)
1 dimensional

Local 0 and 2 dimensional
Take the highest
Global = 2 dimensional

Scaling phenomena

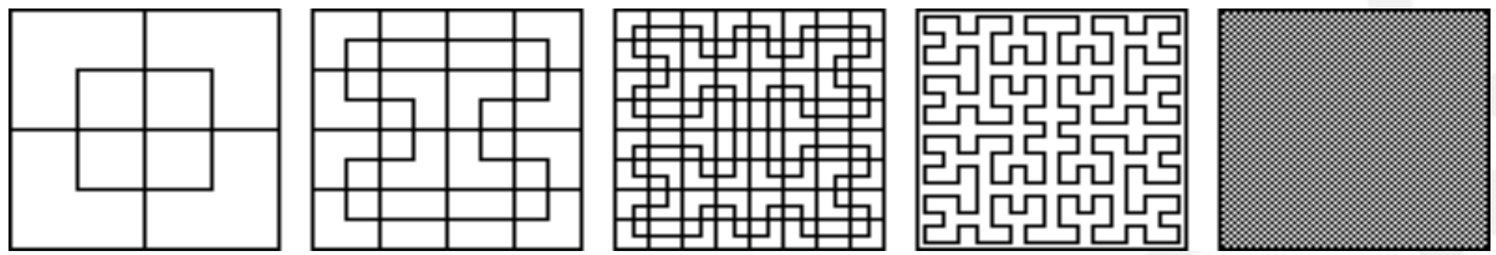
Measuring dimension

Constraint: **The dimension must stay the same over linear transformations**

Consider these linear transformations

Peano's Monster

line-like



plane-like

Koch's Coastline

line-like

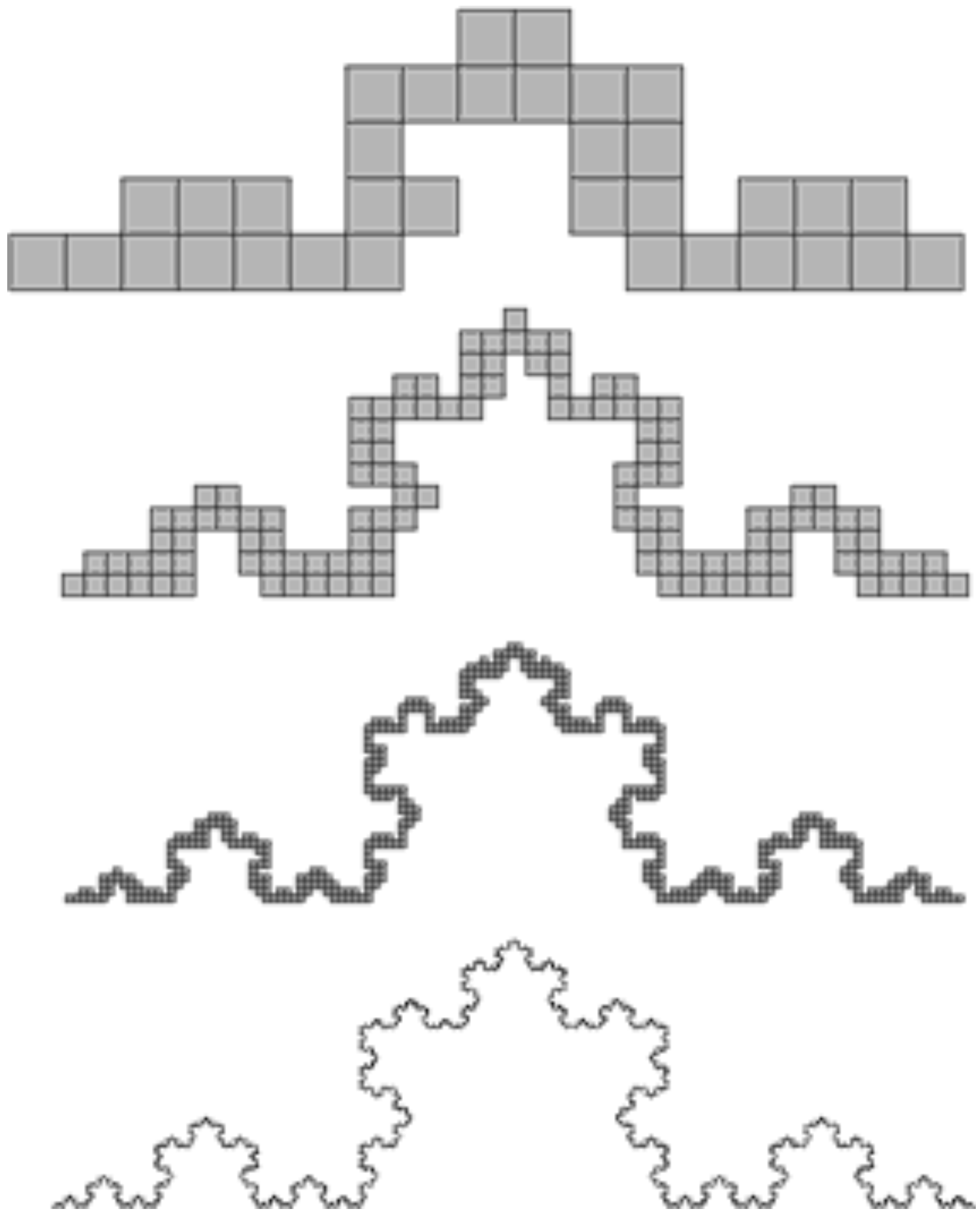
less line-like
(more complex)

Sierpinski's Gasket

plane-like

less plane-like
(more complex)

Solution:
Calculate a “fractional” dimension, e.g. box-counting dimension



Hausdorff-Besicovitch dimension

(box-counting dimension, covering dimension, packing dimension, mass-radius, circle-counting, etc, etc)

$$D = \frac{\log \mathbf{N_h}}{\log 1/\mathbf{h}}$$

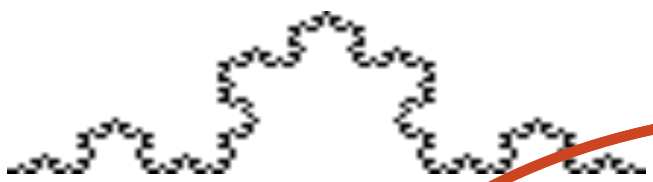
N= number of blocks of size **h** needed to cover the object

Relation between *measure stick* and *measurement outcome*, or: *“scaling of bulk with size”*

Scaling phenomena

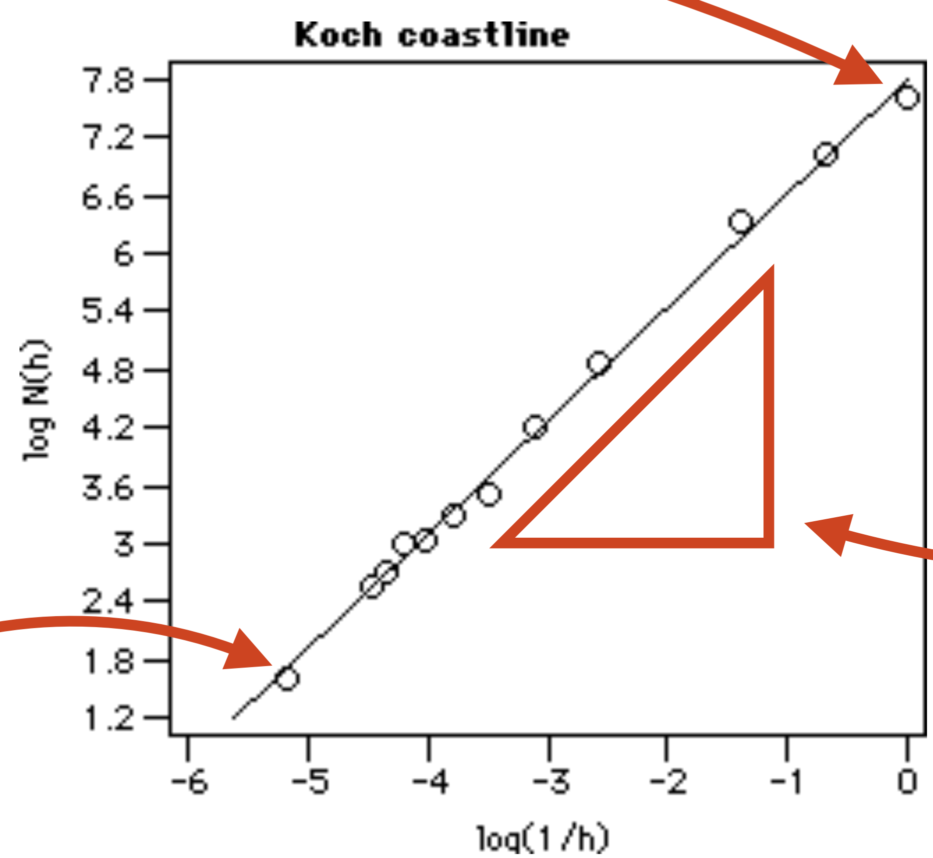
Measuring dimension

Koch Coastline



log (1/h)	log N(h)
0.00	7.61
-0.69	7.04
-1.39	6.33
-2.56	4.86
-3.09	4.22
-3.50	3.53
-3.78	3.30
-4.01	3.04
-4.19	3.00
-4.34	2.71
-4.48	2.56
-5.18	1.61

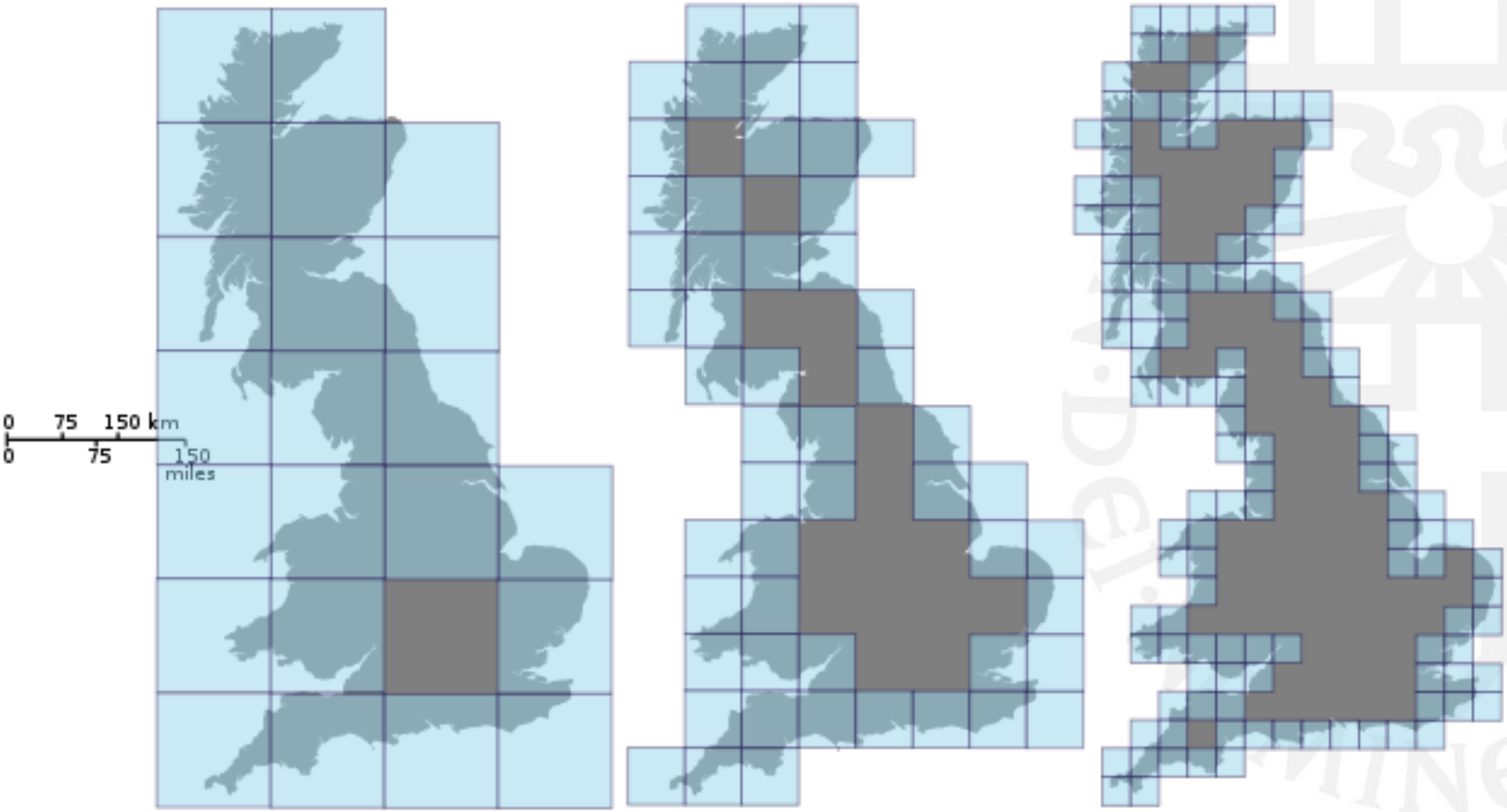
dimension (experimental) = **1.18**
dimension (analytical) = **1.26**
deviation = 6%



Fractal dimension
it's a fraction!

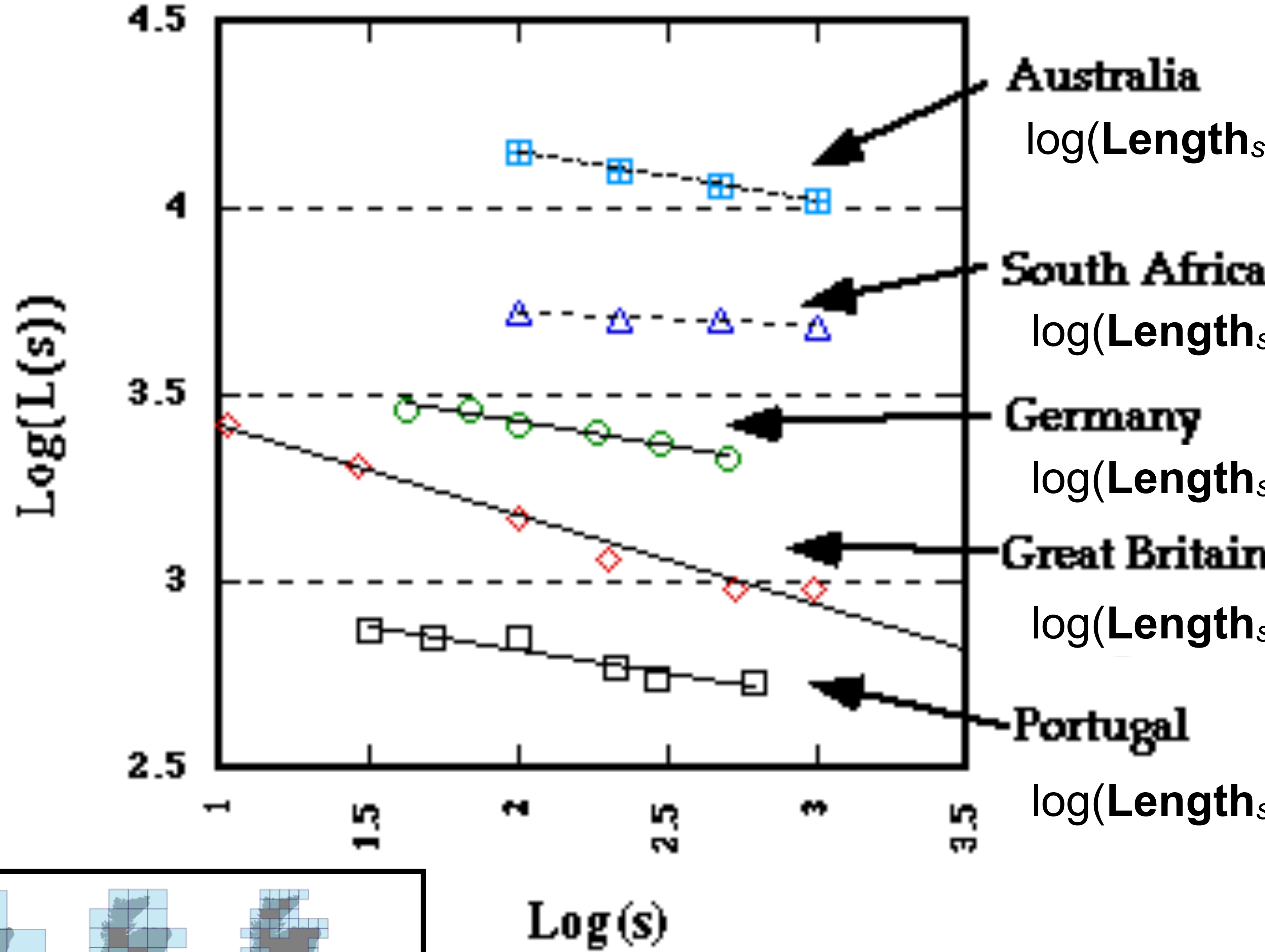
```
Call:
lm(formula = L ~ invS, data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-0.18777 -0.06292  0.02390  0.06059  0.16703

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.79777    0.07318  106.55  < 2e-16 ***
invS         1.17611    0.02109   55.75 8.35e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.'
0.1 ' ' 1

Residual standard error: 0.1137 on 10 degrees of
freedom
Multiple R-squared:  0.9968,    Adjusted R-squared:
0.9965
F-statistic:  3109 on 1 and 10 DF,  p-value: 8.355e-14
```

How to describe scaling relations: Calculate a “fractional” dimension, e.g. box-counting dimension



Scaling phenomena

$\log(\mathbf{Length}_{scale}) = b*\log(scale)+a$



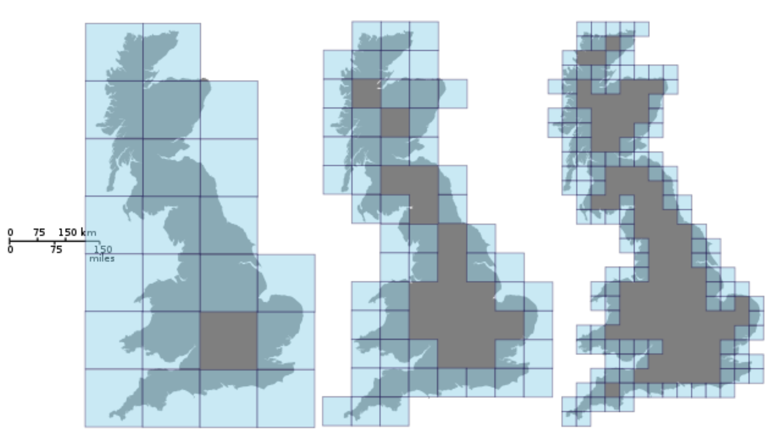
Australia: $\log(\mathbf{Length}_s) = -.13*\log(s)+4.4$

South Africa: $\log(\mathbf{Length}_s) = \mathbf{-.03}*\log(s)+3.8$

Germany: $\log(\mathbf{Length}_s) = -.12*\log(s)+3.7$

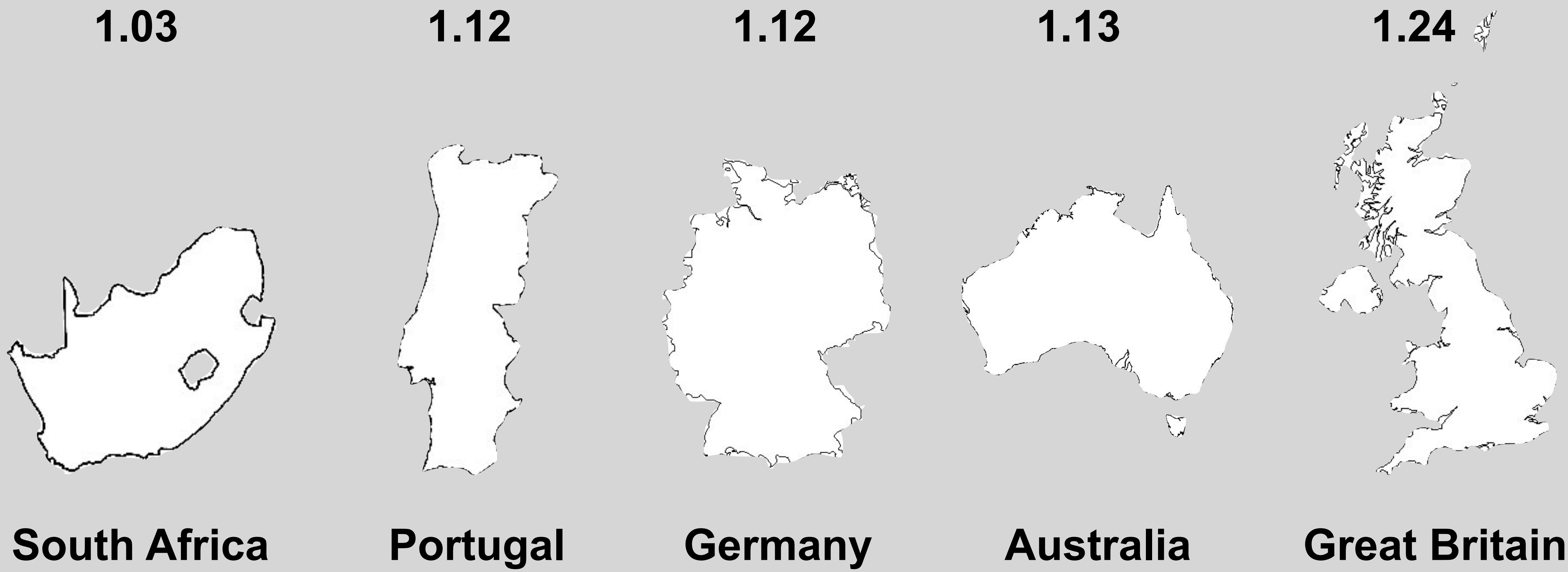
Great Britain: $\log(\mathbf{Length}_s) = \mathbf{-.24}*\log(s)+3.4$

Portugal: $\log(\mathbf{Length}_s) = -.12*\log(s)+3.3$



Scaling phenomena

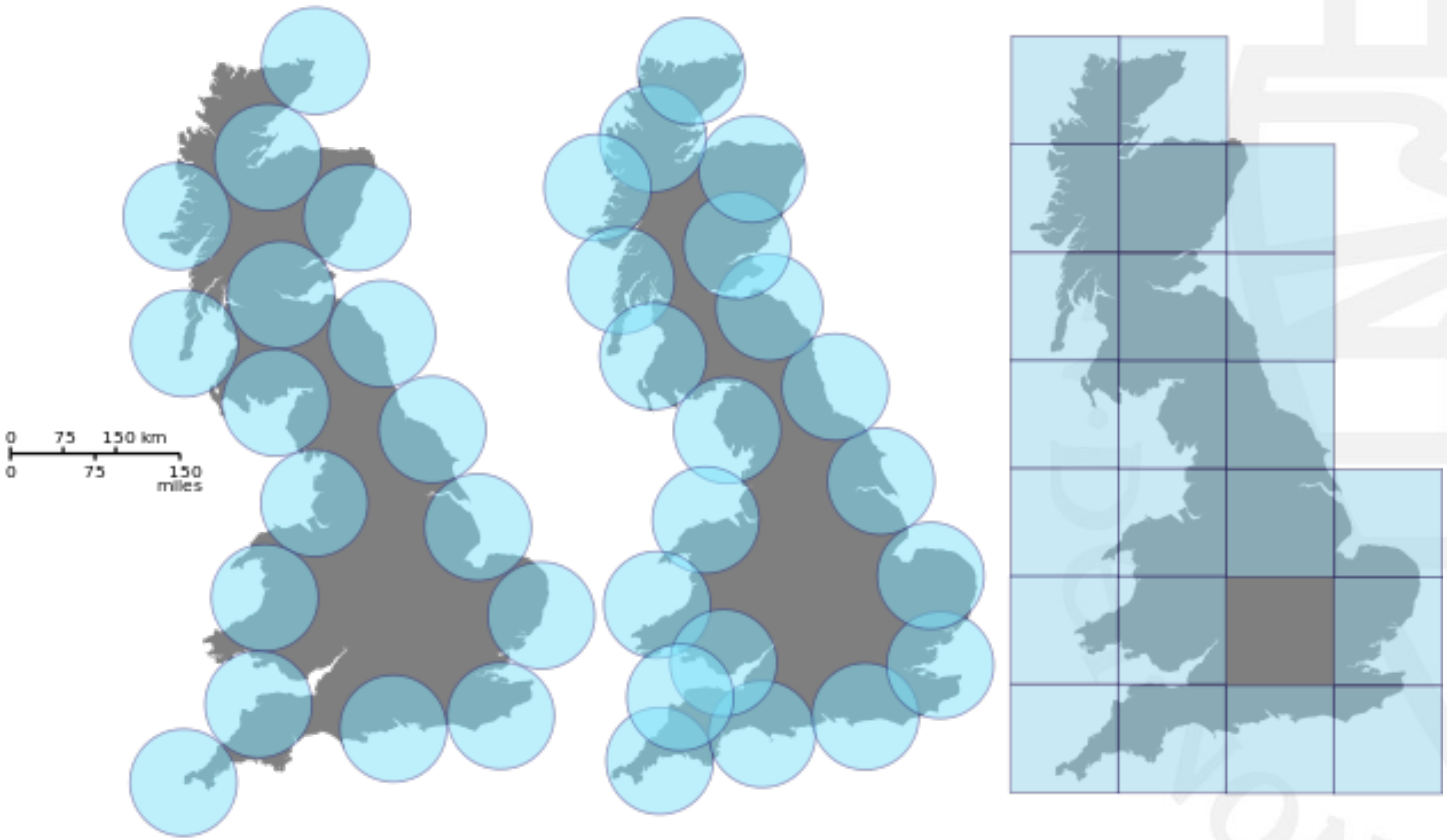
Scaling and Complexity



Ordered by scaling exponent, the log-log slope

Scaling phenomena

Many variants of “covering” dimensions



ball packing < ball covering < box covering

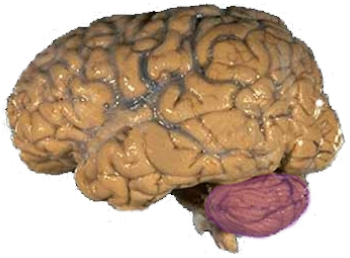
Scaling phenomena

Measuring dimension

Packing Cubes or Spheres and Wrapping Blankets:

3D spatial scaling relations in nature - Cauliflower
Fractal dimension = 2.33

Surface of human brain: 2.79



Surface of human lungs: 2.97

Dynamics of Complex Systems

Scaling

Fractal Geometry

Fluctuation Analysis:

SDA
DFA
PSD

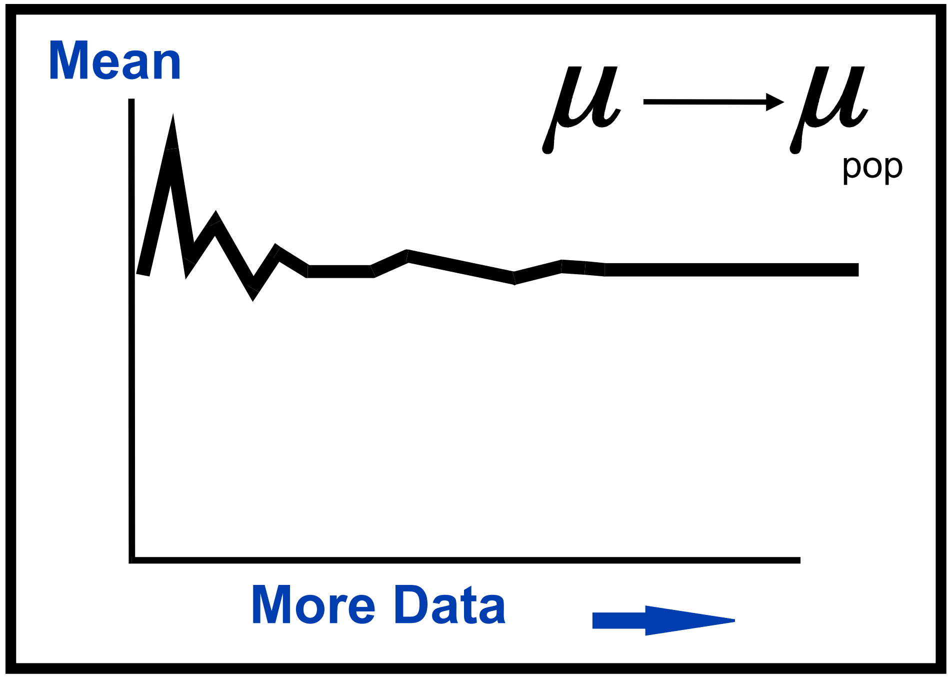
Scaling phenomena: Time scales

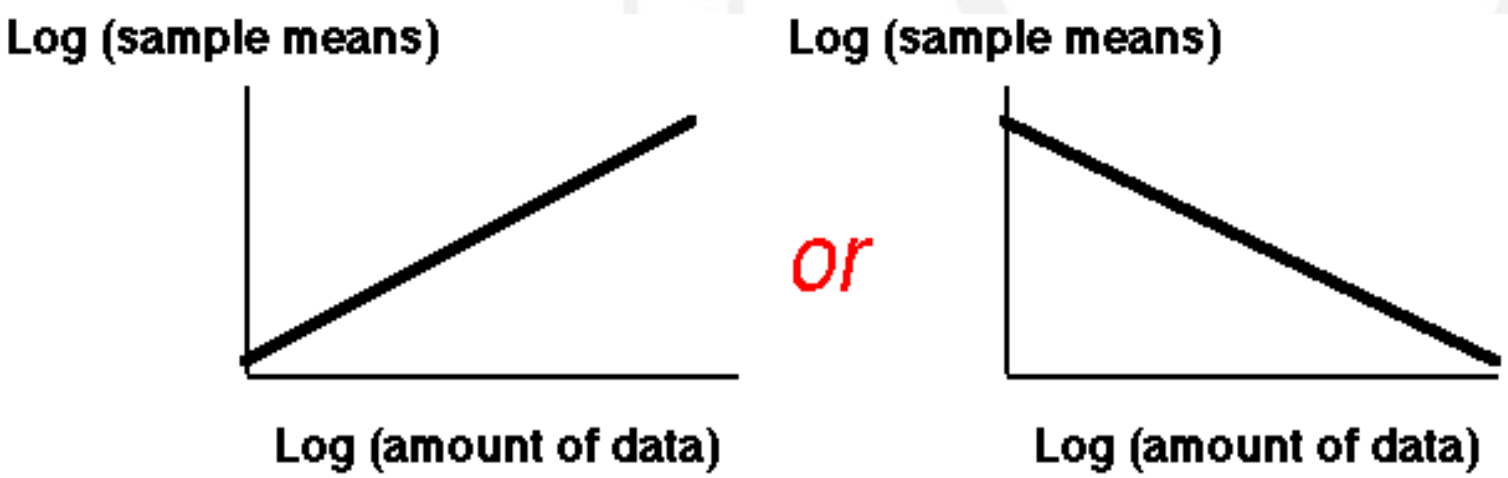
Independent observations of random variables

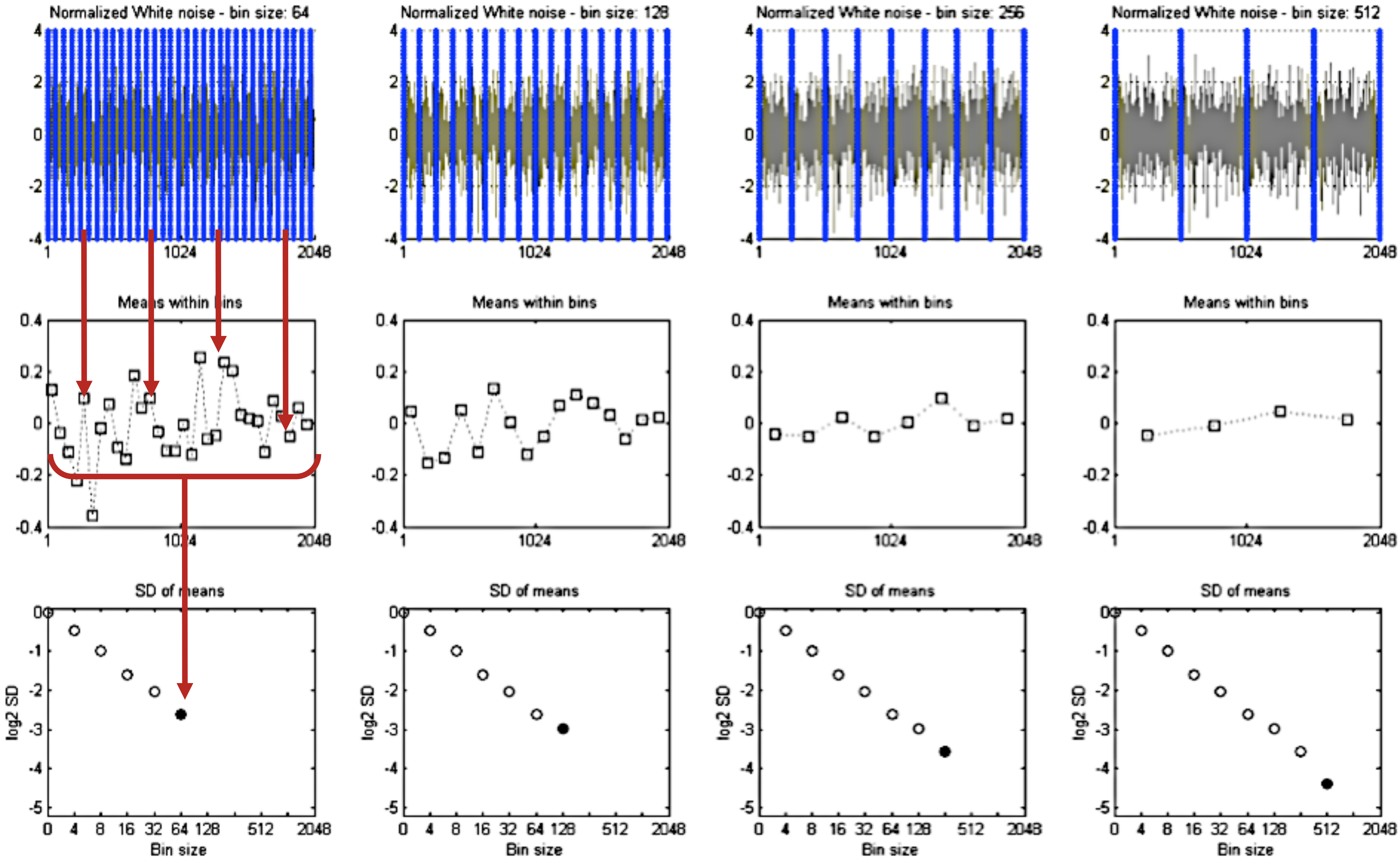
μ±σ are sufficient to characterise absence of dependencies in the data:
e.g. Expected value of **μ** for **N** = 100, given **σ**
N = ensemble size

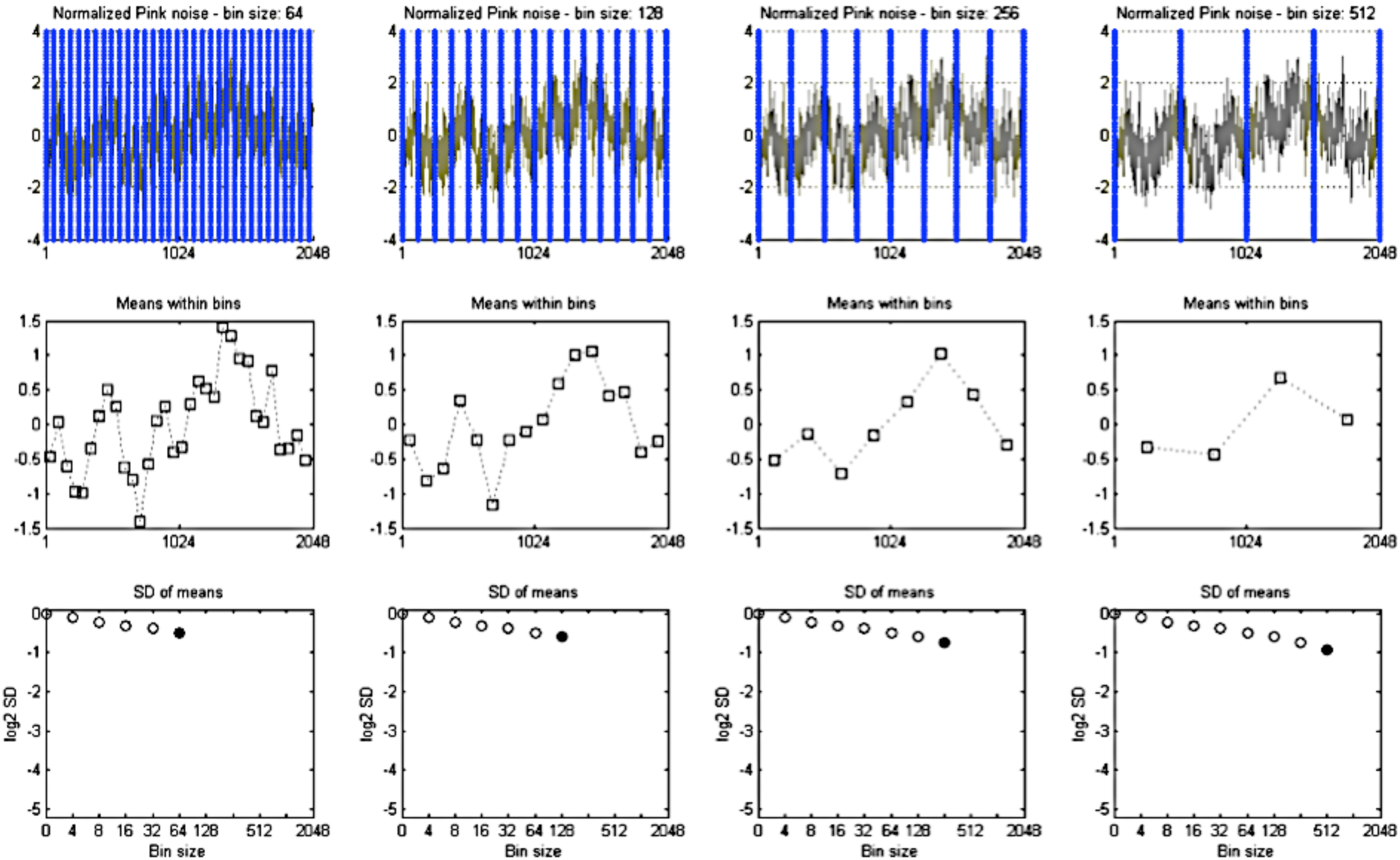
Interdependent observations across different scales

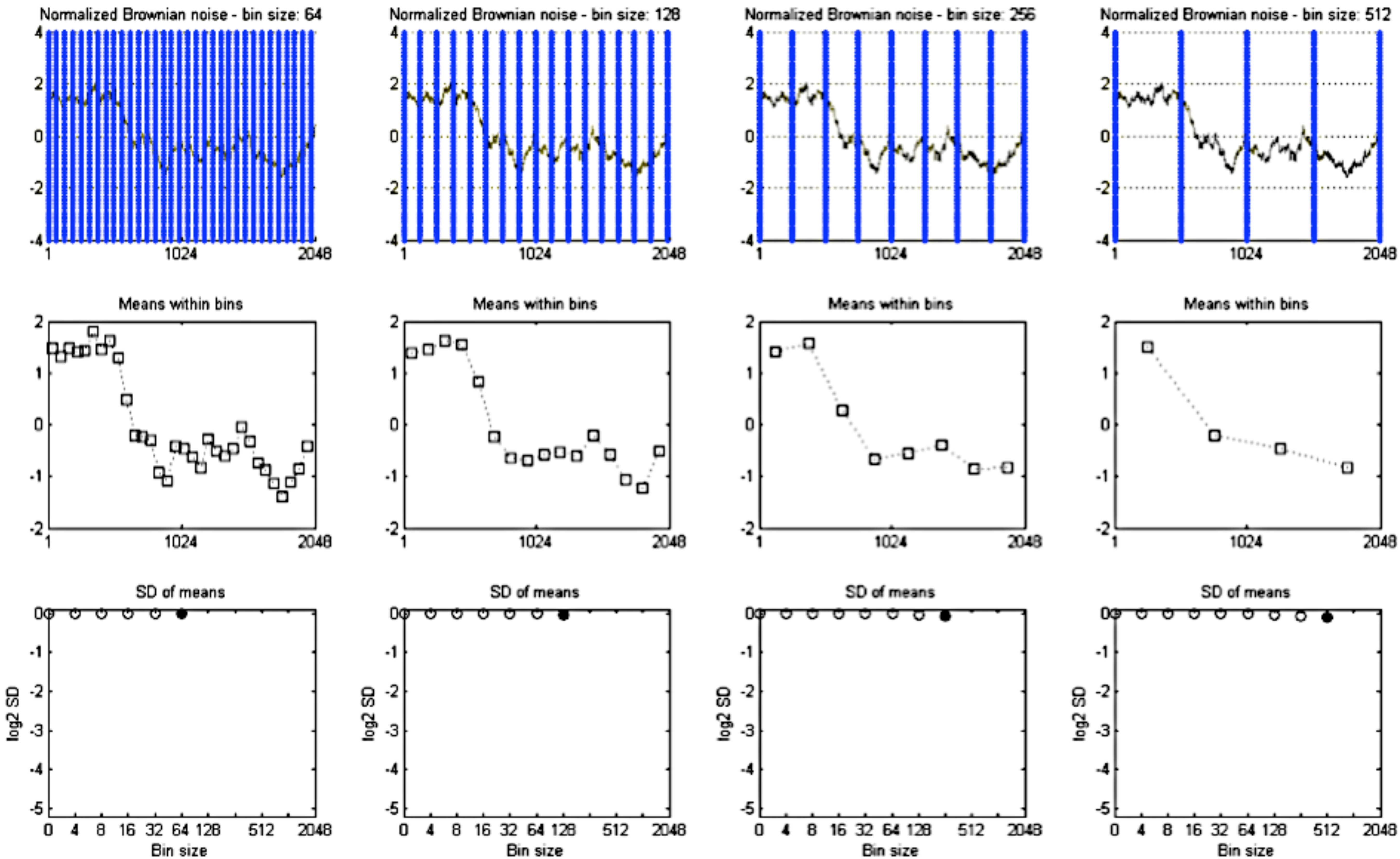
μ±σ are insufficient to characterise dependencies in the data:
e.g. Sample estimates of **μ** change with **N**
N = observation time






Normalized White noise - bin size: 64
Normalized White noise - bin size: 128
Normalized White noise - bin size: 256
Normalized White noise - bin size: 512
Means within bins
SD of means
log2 SD
Bin size
1
1024
2048
0
4
8
16
32
64
128
512


Normalized Pink noise - bin size: 64
Normalized Pink noise - bin size: 128
Normalized Pink noise - bin size: 256
Normalized Pink noise - bin size: 512
Means within bins
Means within bins
Means within bins
Means within bins
SD of means
SD of means
SD of means
SD of means
log2 SD
Bin size


Normalized Brownian noise - bin size: 64
Normalized Brownian noise - bin size: 128
Normalized Brownian noise - bin size: 256
Normalized Brownian noise - bin size: 512
Means within bins
SD of means
log2 SD
Bin size

Detrended Fluctuation Analysis

Same logic as SDA except:

- **A.** Signal is integrated

- **B.** Divided into bins

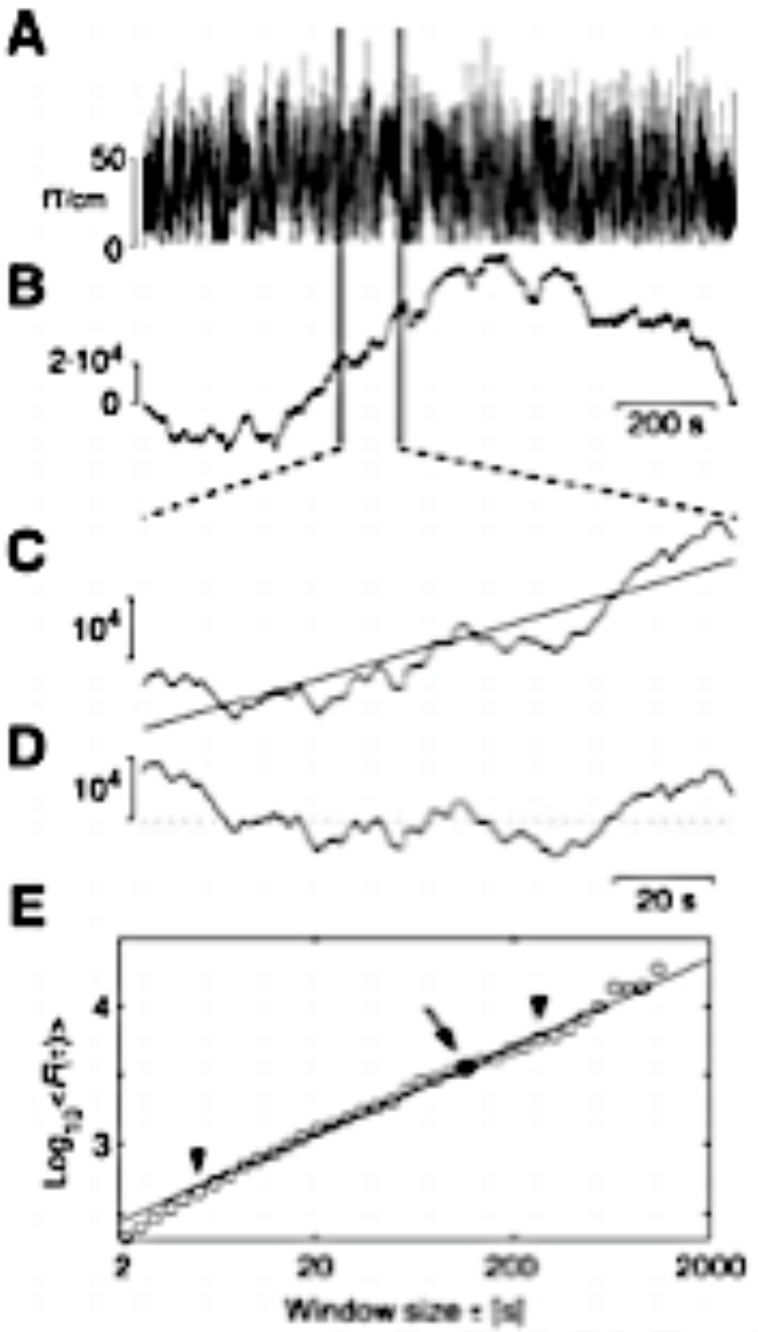
- **C.** Detrended (linear)

- **D.** Remaining SD is the dispersion measure

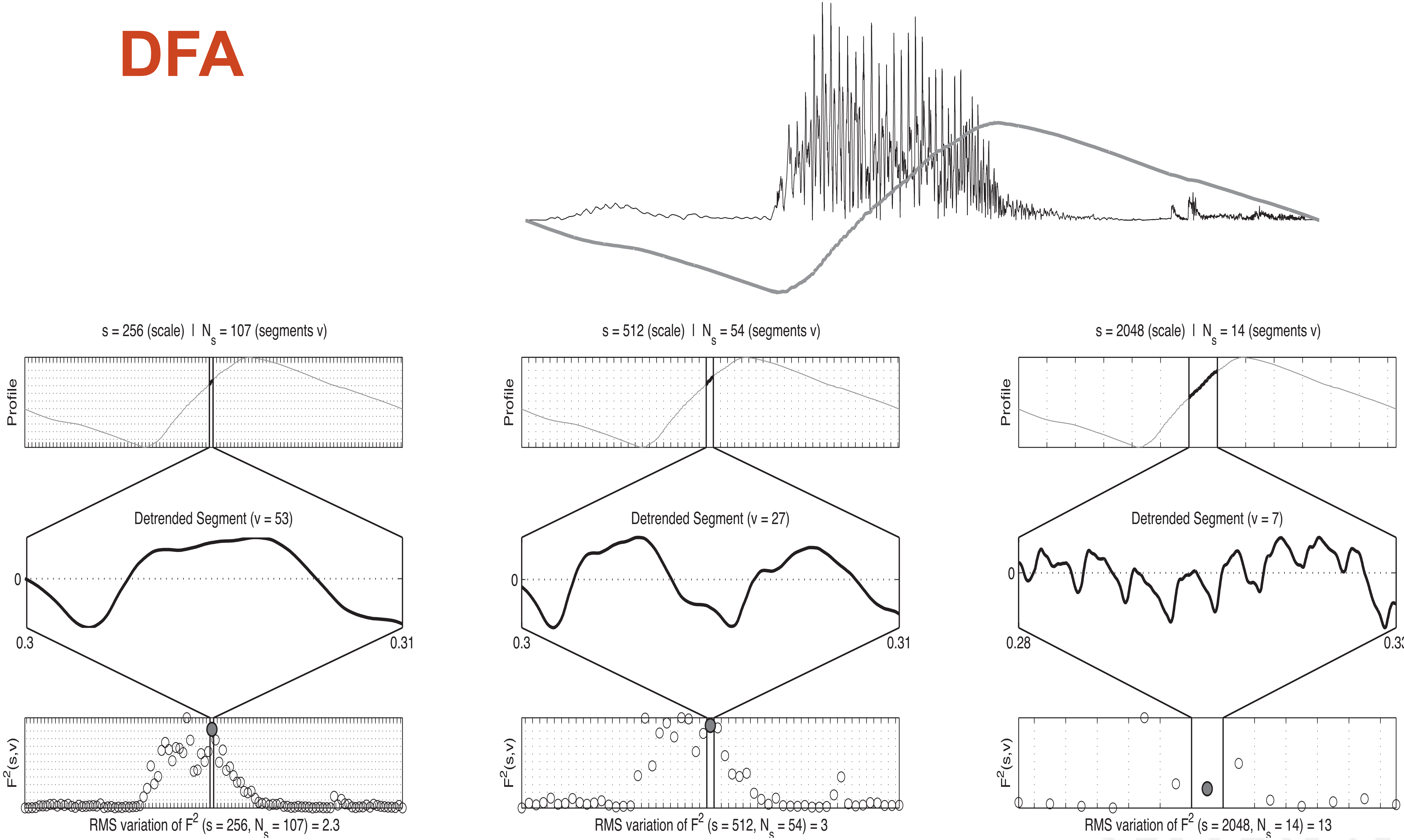
- **E.** Plot on Log_{10} scale and calculate slope (alpha)

- FD = 2 - (slope)

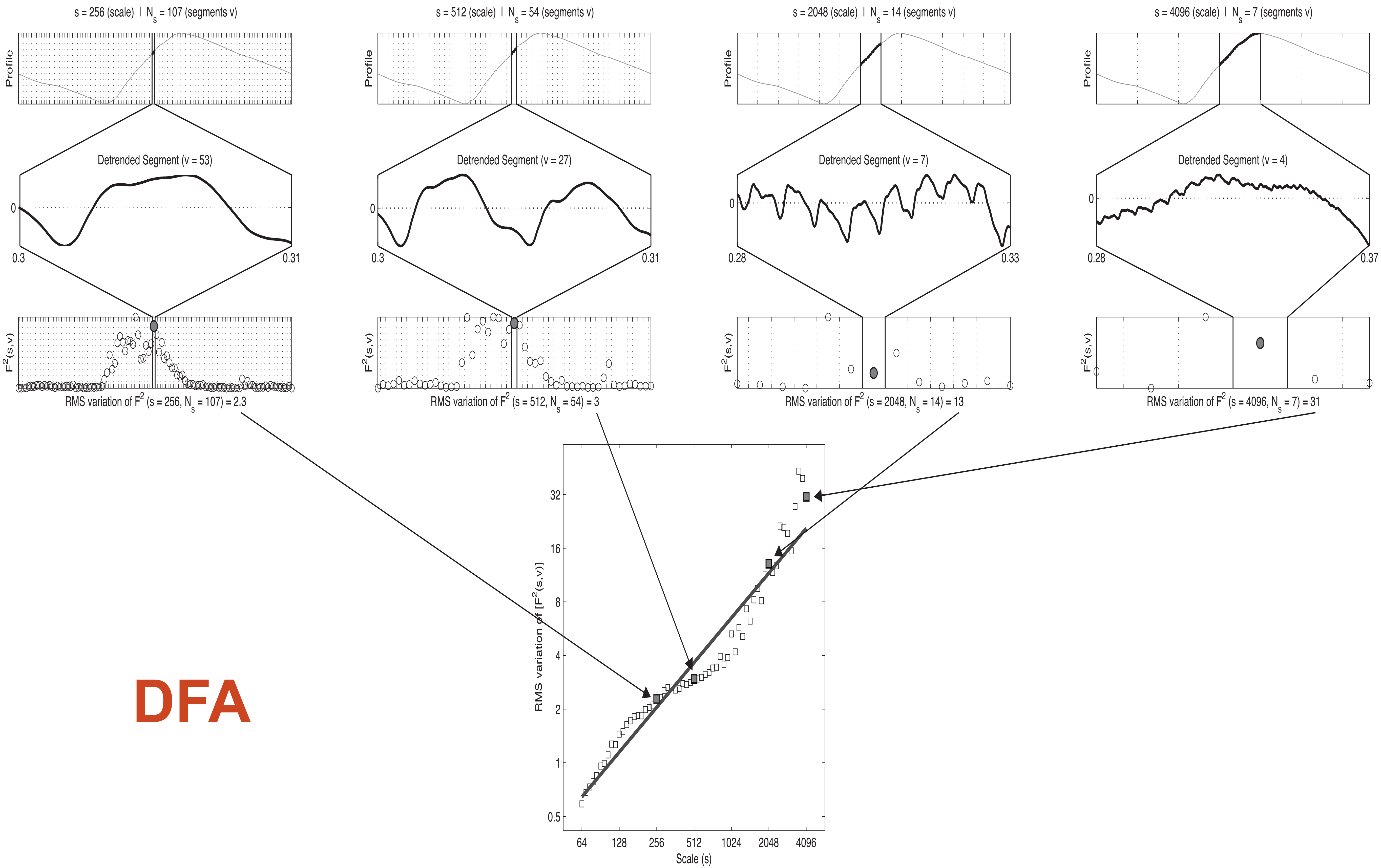
Or **C** & **D** in one step: fit a line in the bin and take SD of residuals… same result.



DFA

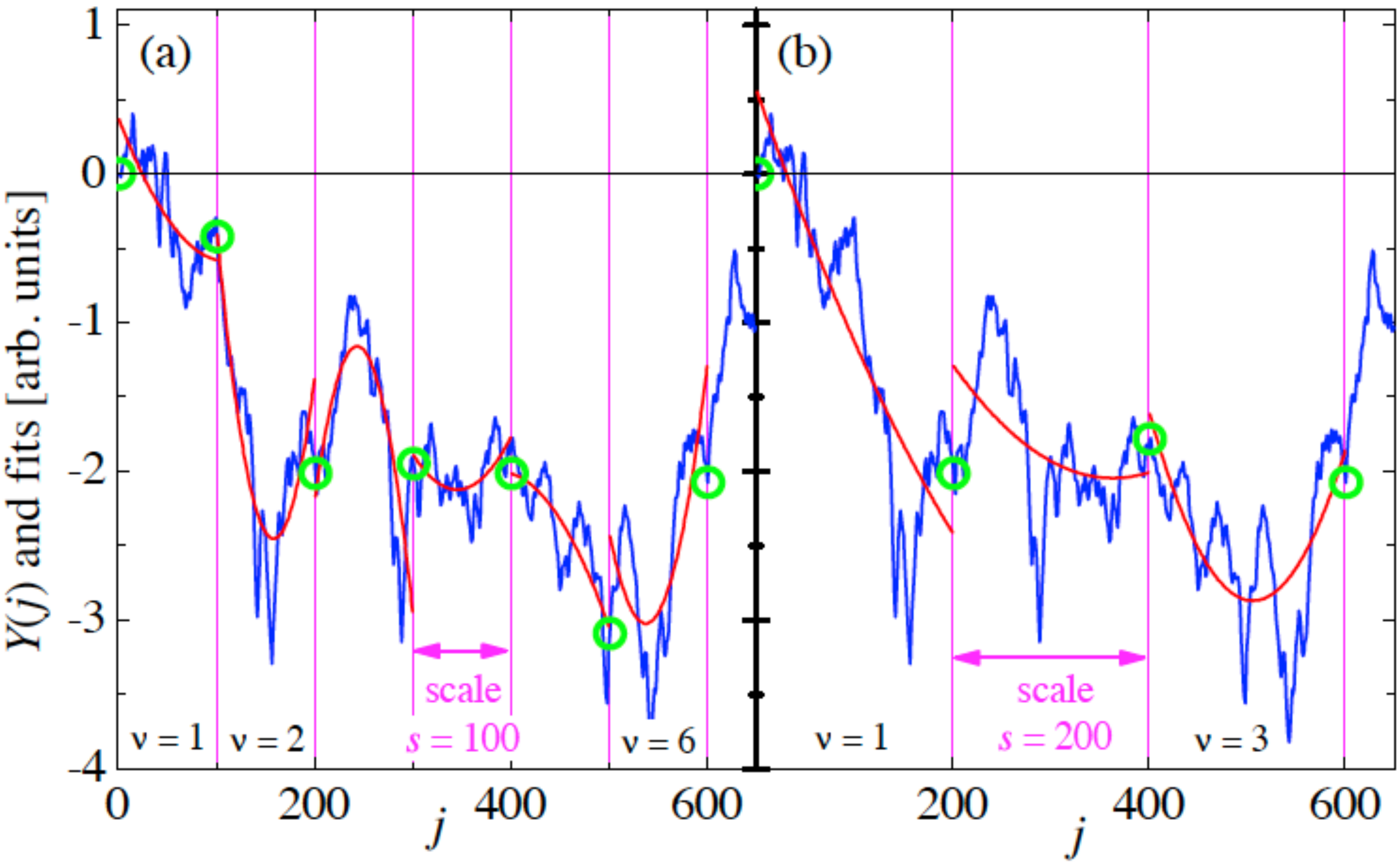


s = 256 (scale) | N_s = 107 (segments v)
s = 512 (scale) | N_s = 54 (segments v)
s = 2048 (scale) | N_s = 14 (segments v)
Profile
Detrended Segment (v = 53)
Detrended Segment (v = 27)
Detrended Segment (v = 7)
0
0.3
0.31
0.28
0.33
F²(s,v)
RMS variation of F² (s = 256, N_s = 107) = 2.3
RMS variation of F² (s = 512, N_s = 54) = 3
RMS variation of F² (s = 2048, N_s = 14) = 13

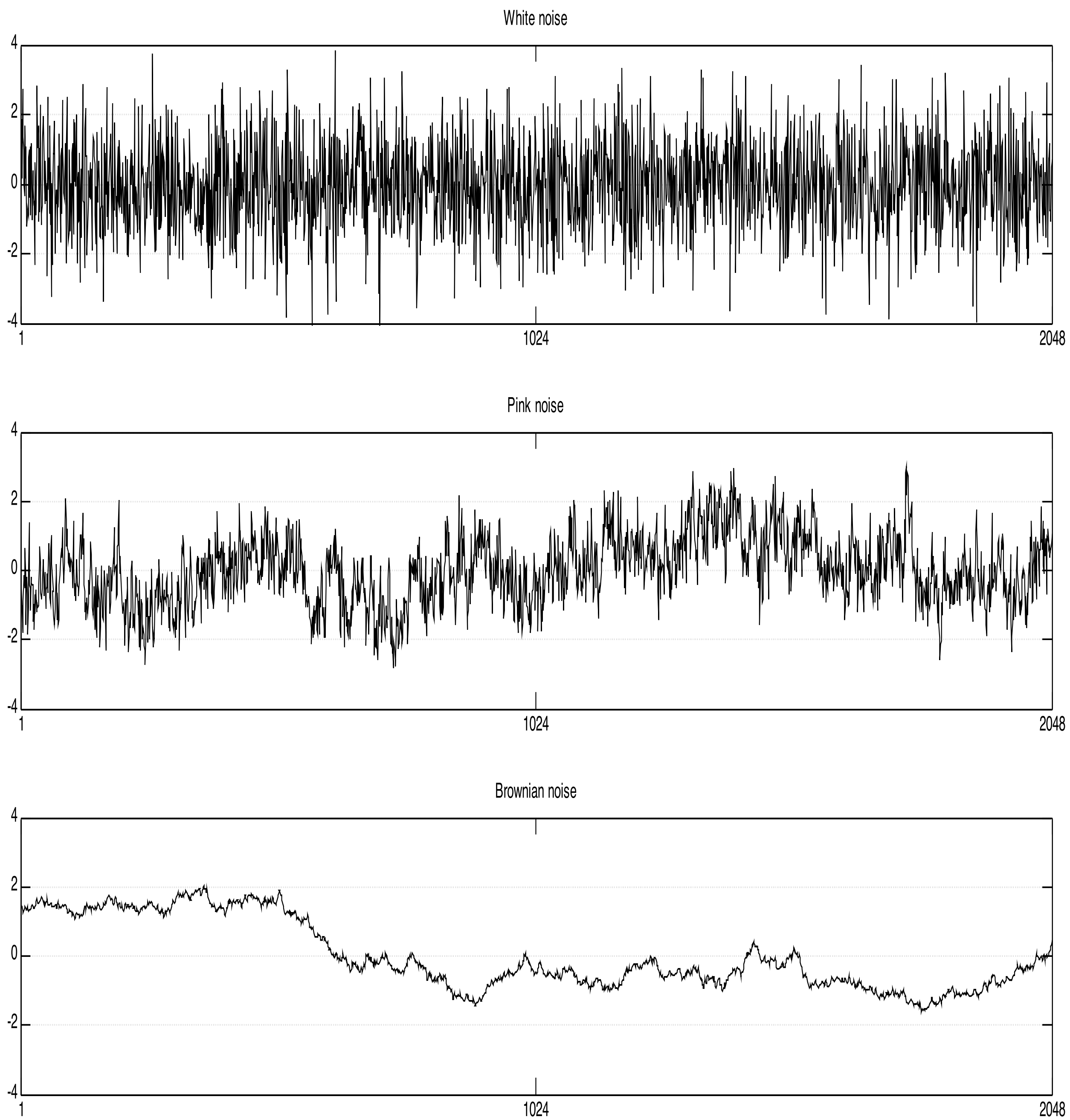

s = 256 (scale) I N_s = 107 (segments v)
s = 512 (scale) I N_s = 54 (segments v)
s = 2048 (scale) I N_s = 14 (segments v)
s = 4096 (scale) I N_s = 7 (segments v)
Profile
Detrended Segment (v = 53)
Detrended Segment (v = 27)
Detrended Segment (v = 7)
Detrended Segment (v = 4)
F2(s,v)
RMS variation of F2 (s = 256, N_s = 107) = 2.3
RMS variation of F2 (s = 512, N_s = 54) = 3
RMS variation of F2 (s = 2048, N_s = 14) = 13
RMS variation of F2 (s = 4096, N_s = 7) = 31
RMS variation of [F2(s,v)]
Scale (s)

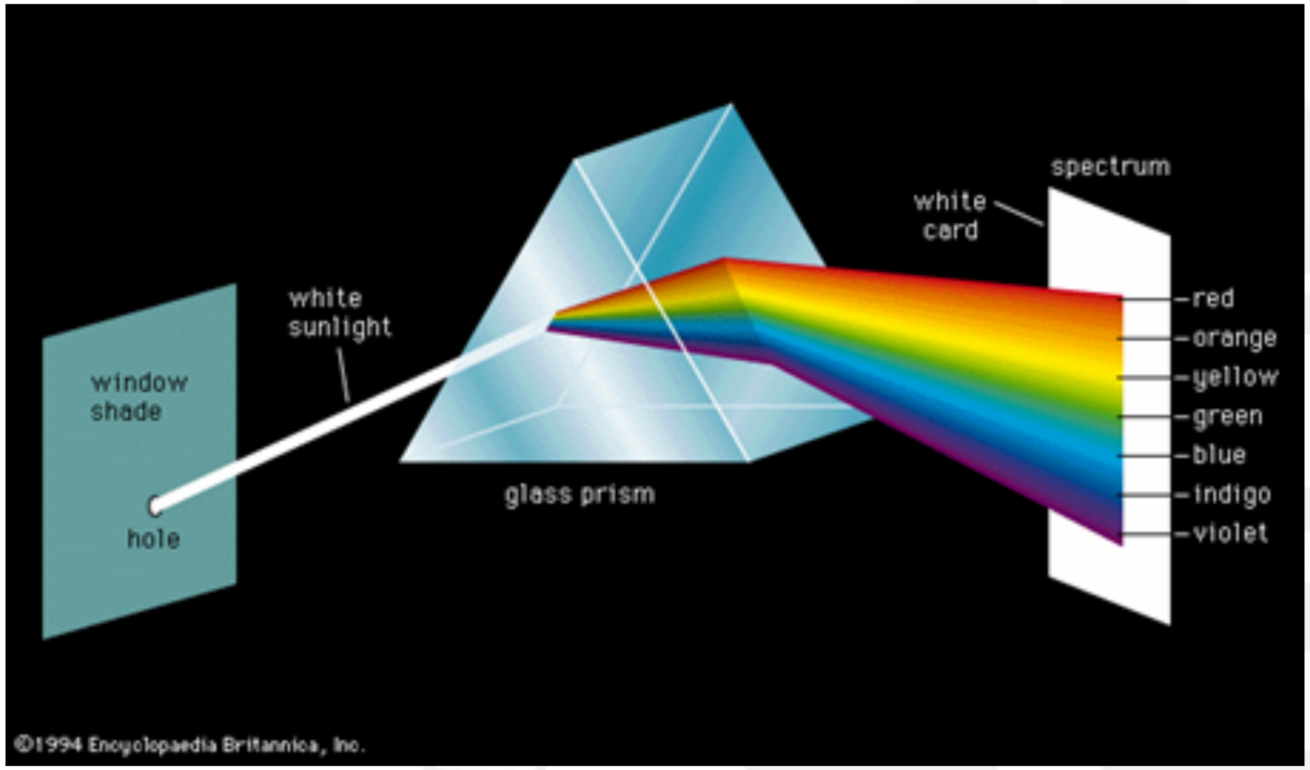
DFA

Detrended Fluctuation Analysis: Different ‘orders’ of detrending



Spectral analysis: Frequencies in the signal



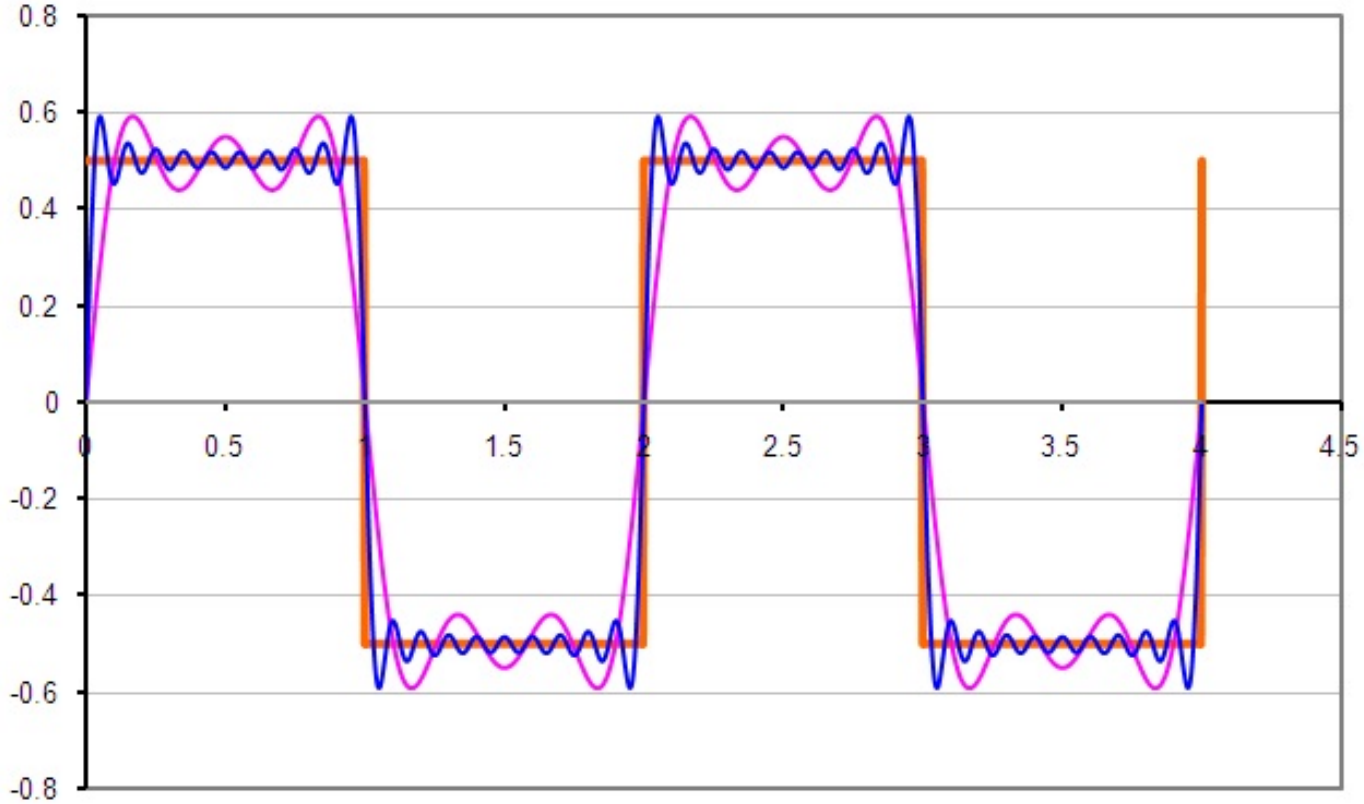


Characterize a signal by its dominant frequencies: Spectral analysis-Fourier transform

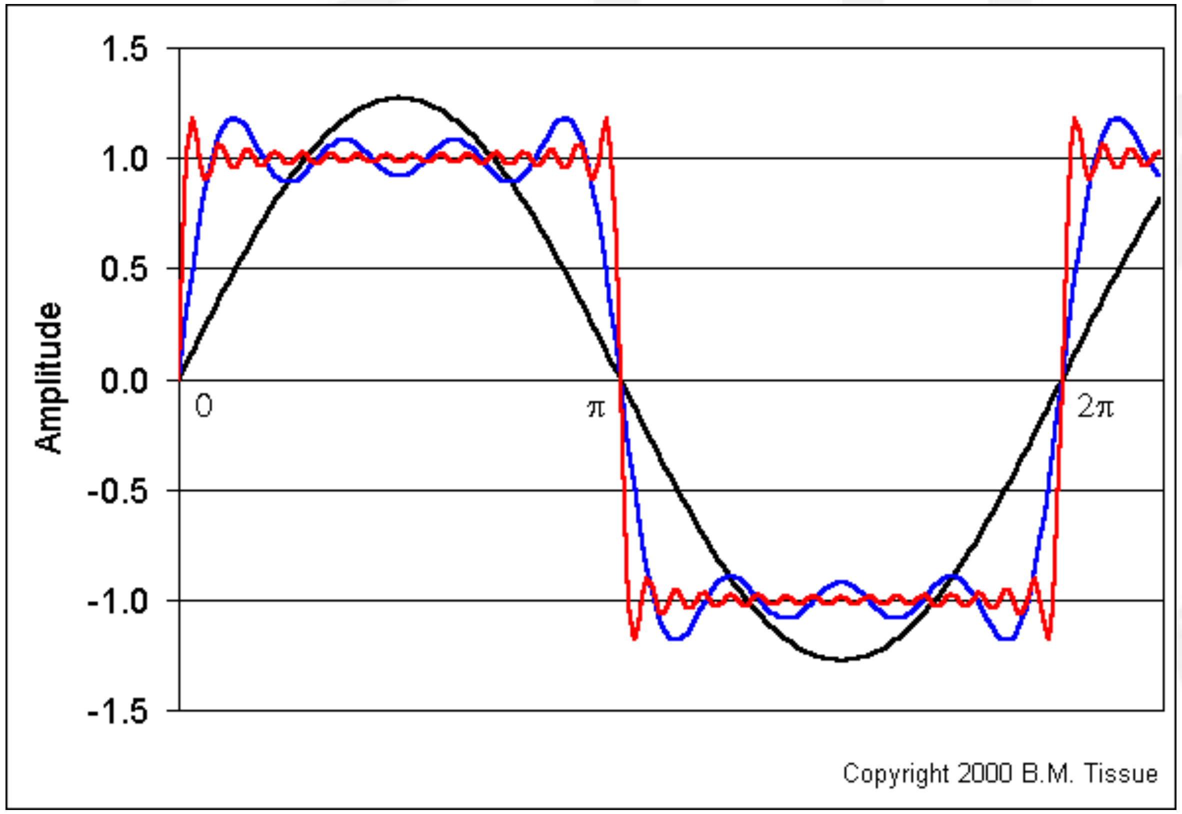
$$g(t) = a_0 + \sum_{m=1}^{\infty} a_m \cos\left(\frac{2\pi mt}{T}\right) + \sum_{n=1}^{\infty} b_n \sin\left(\frac{2\pi nt}{T}\right)$$

$$= \sum_{m=0}^{\infty} a_m \cos\left(\frac{2\pi mt}{T}\right) + \sum_{n=1}^{\infty} b_n \sin\left(\frac{2\pi nt}{T}\right)$$

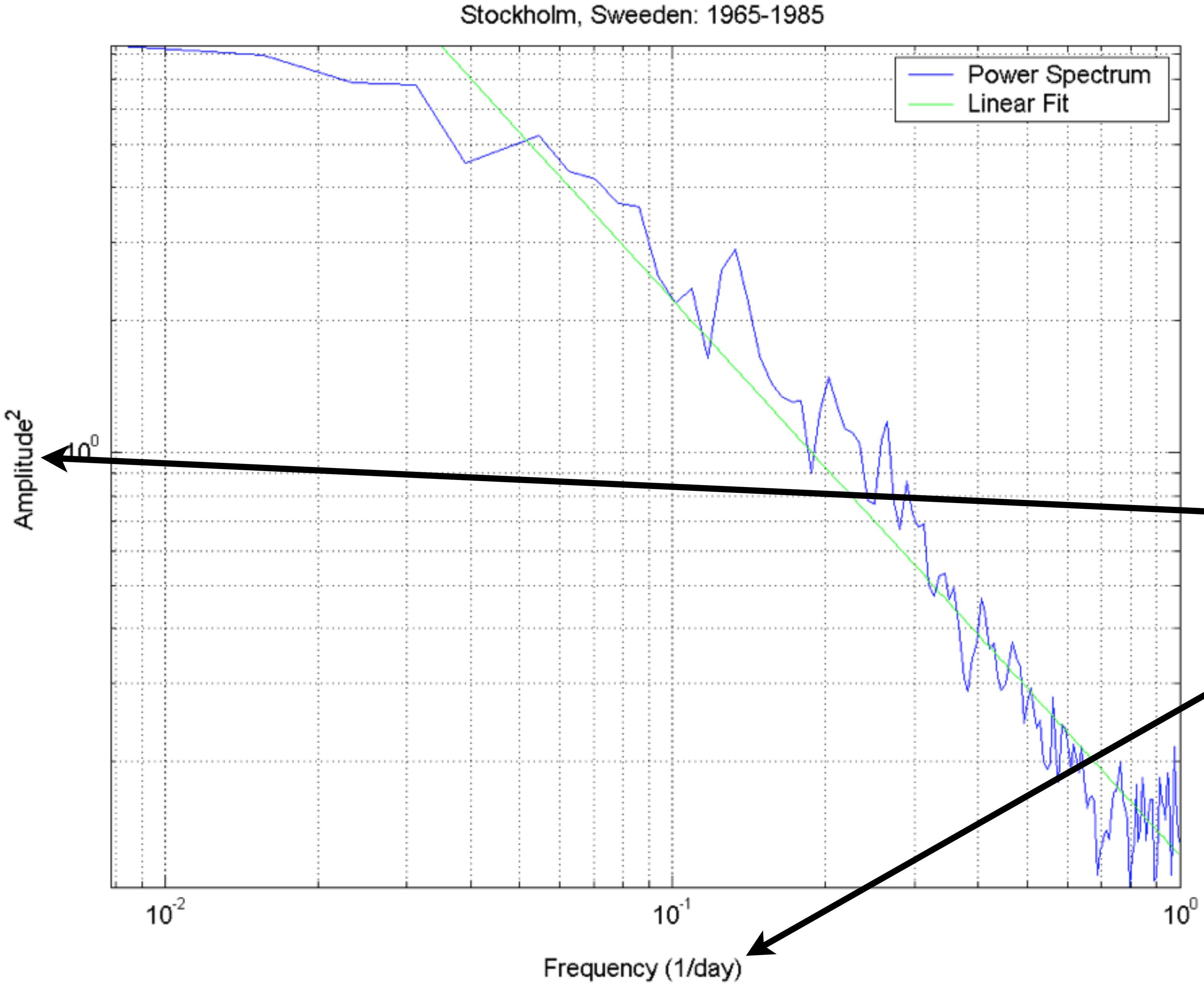
Spectral analysis: Fourier transform



Reconstruct a waveform by adding many sine and cosine waves of different frequencies and amplitudes

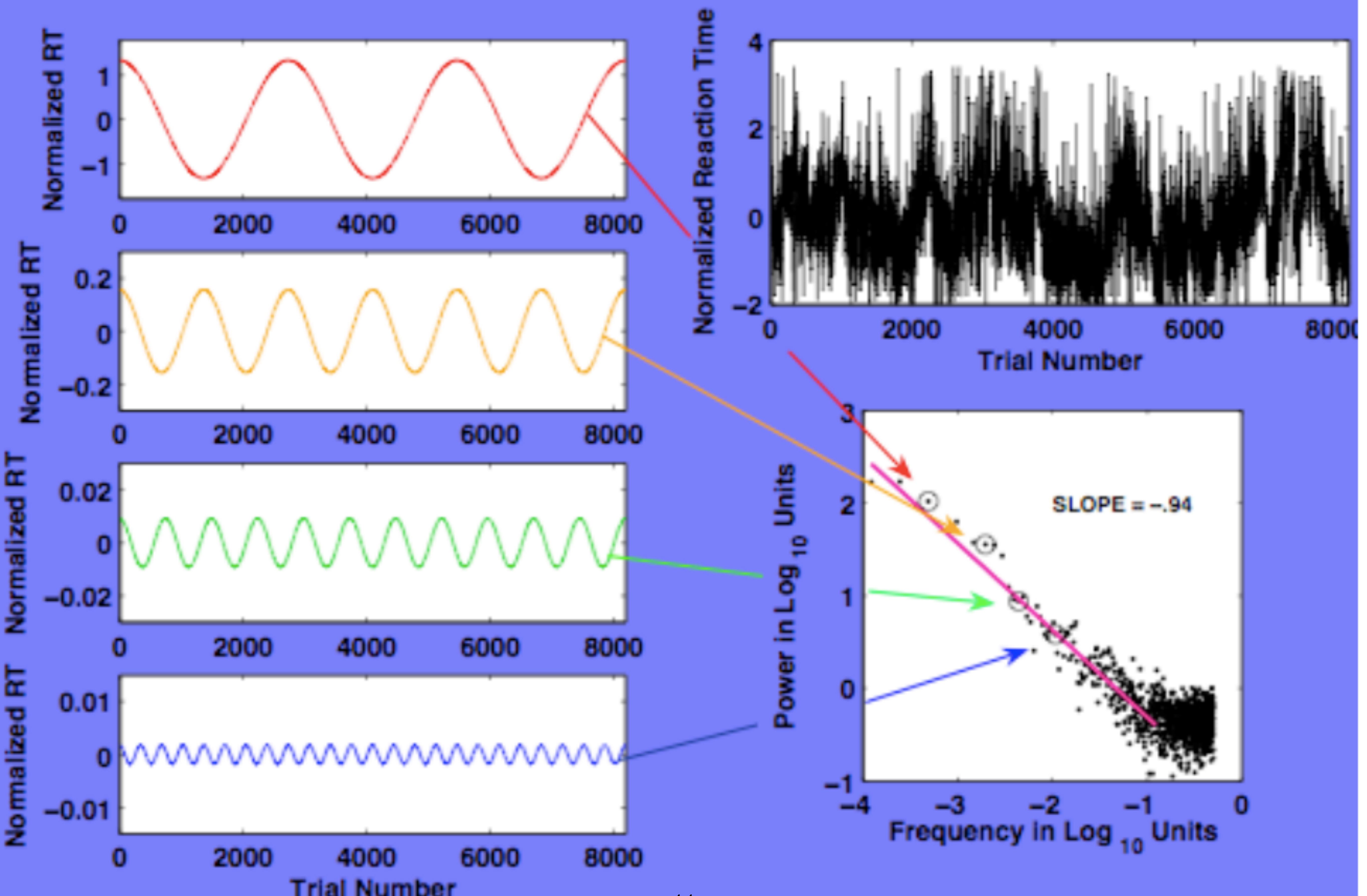


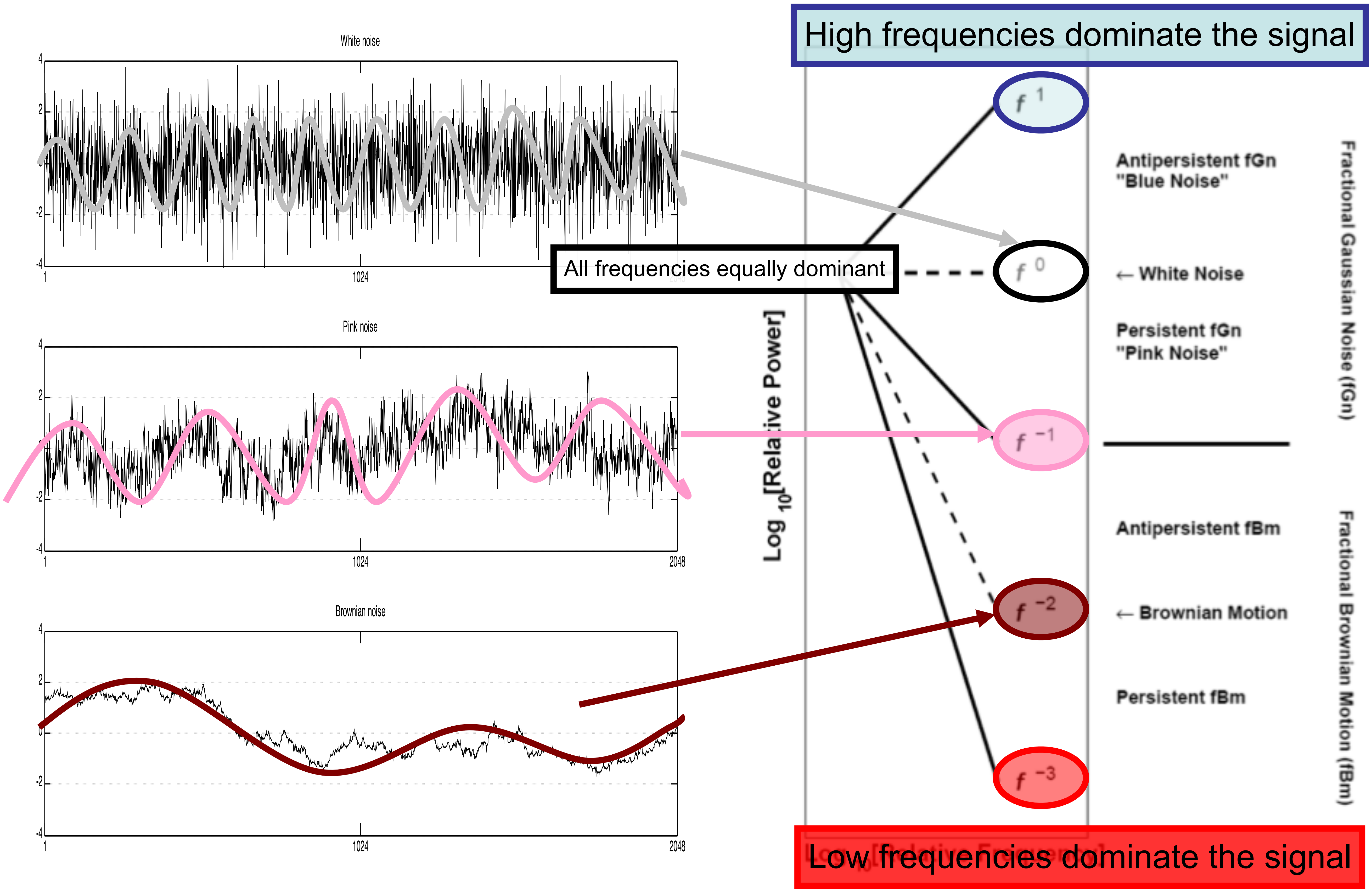
Spectral analysis: Fourier transform -> Frequency domain



Reconstruct a waveform by adding many sine and cosine waves of different **frequencies** and **amplitudes**

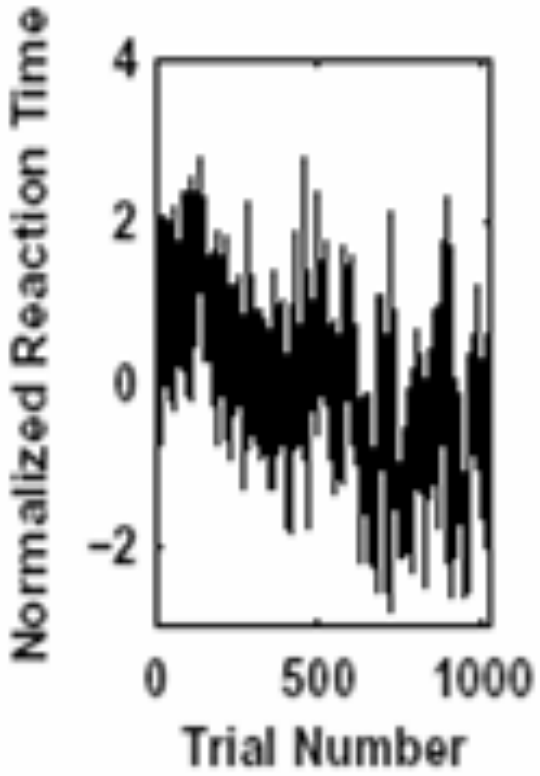
Fractal Time: Scale Free Variation in Repeated Measures

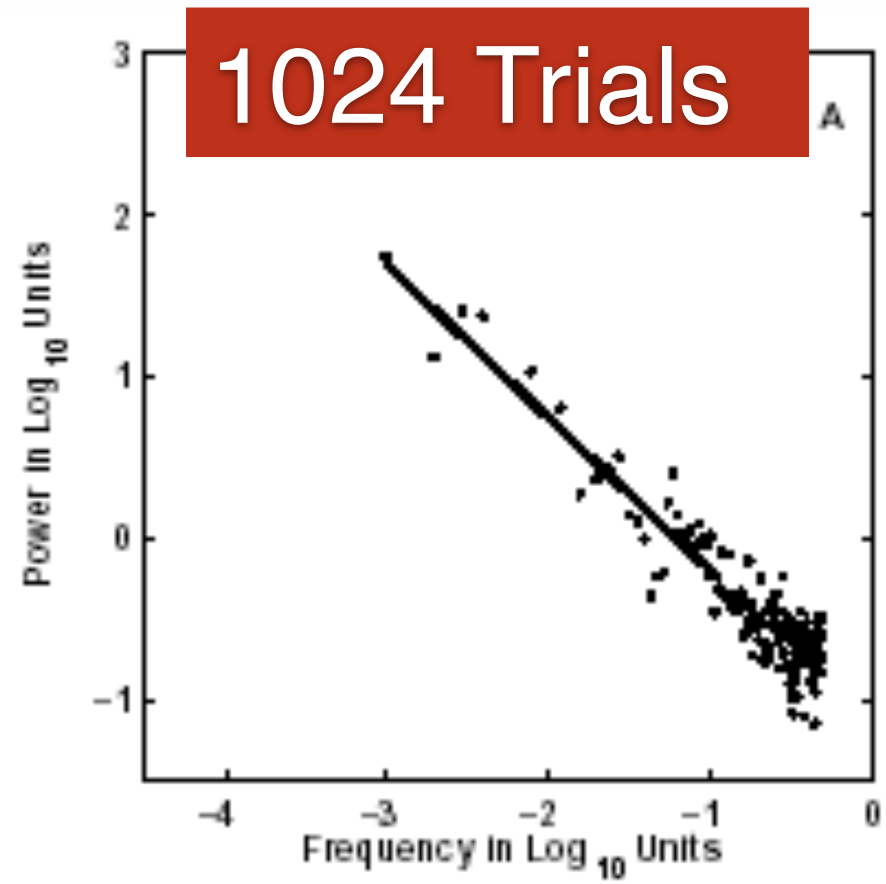


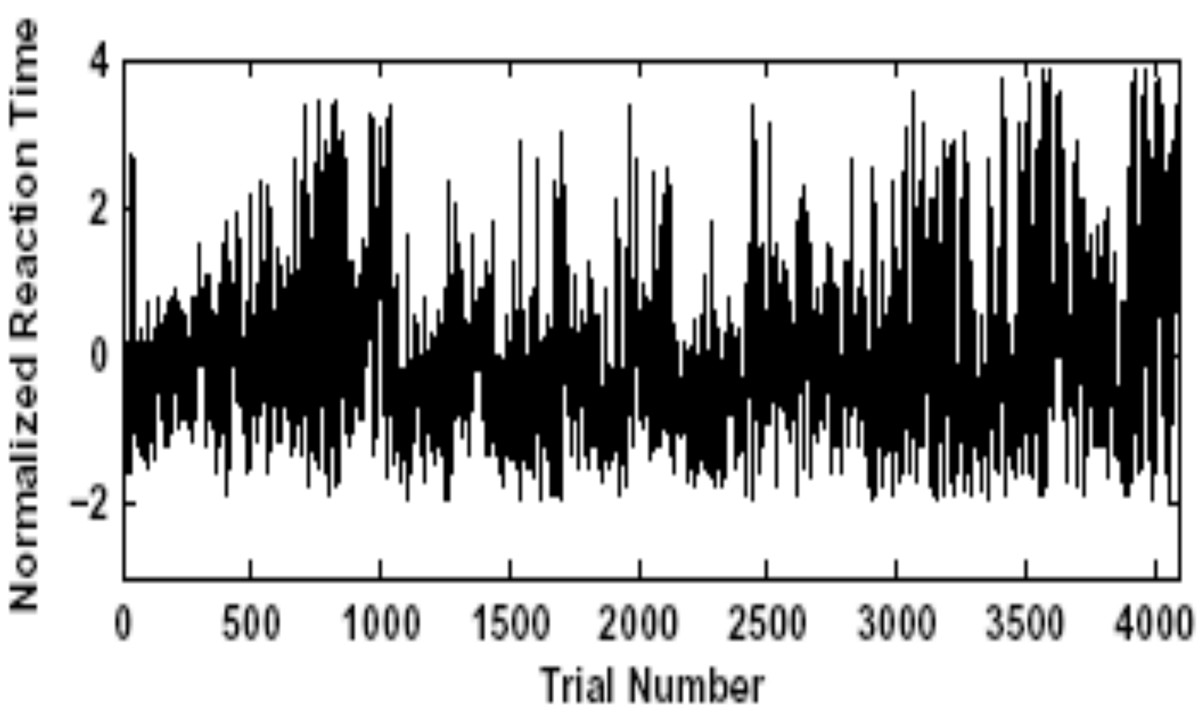


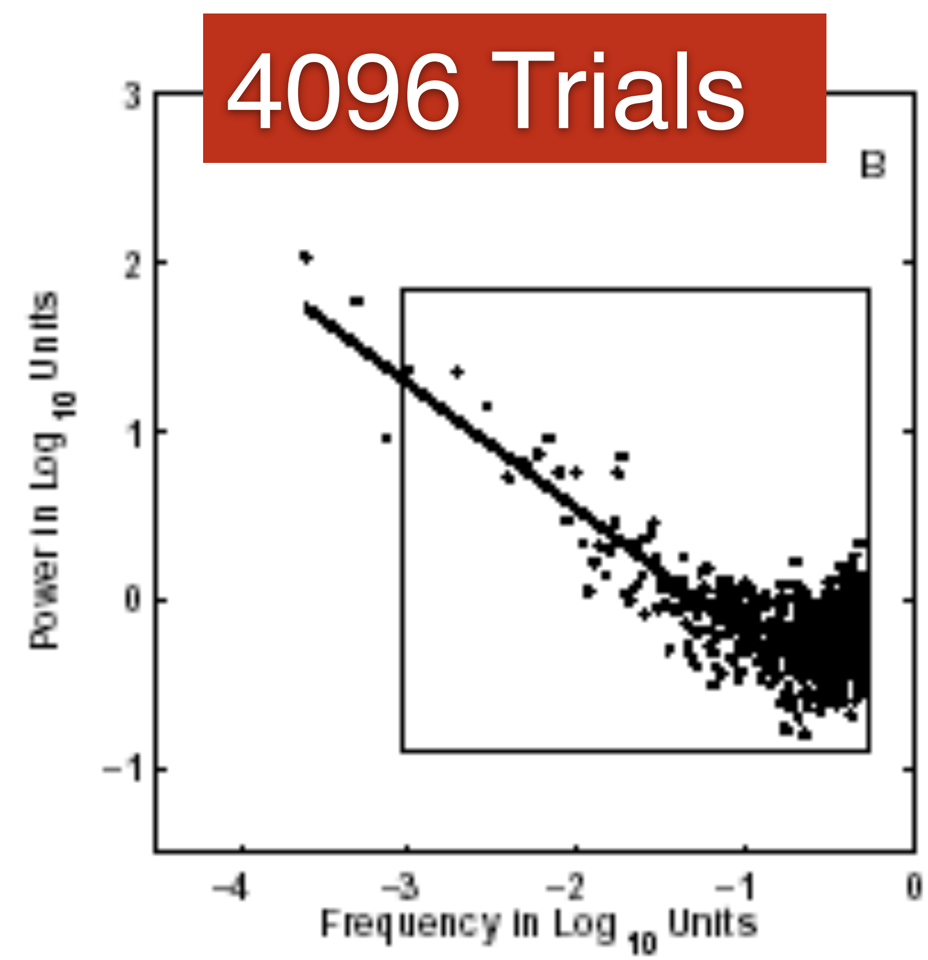
High frequencies dominate the signal
White noise
Pink noise
Brownian noise
All frequencies equally dominant
f^{1}
f^{0}
f^{-1}
f^{-2}
f^{-3}
$\log_{10}$[Relative Power]
Antipersistent fGn
"Blue Noise"
← White Noise
Persistent fGn
"Pink Noise"
Antipersistent fBm
← Brownian Motion
Persistent fBm
Fractional Gaussian Noise (fGn)
Fractional Brownian Motion (fBm)
Low frequencies dominate the signal

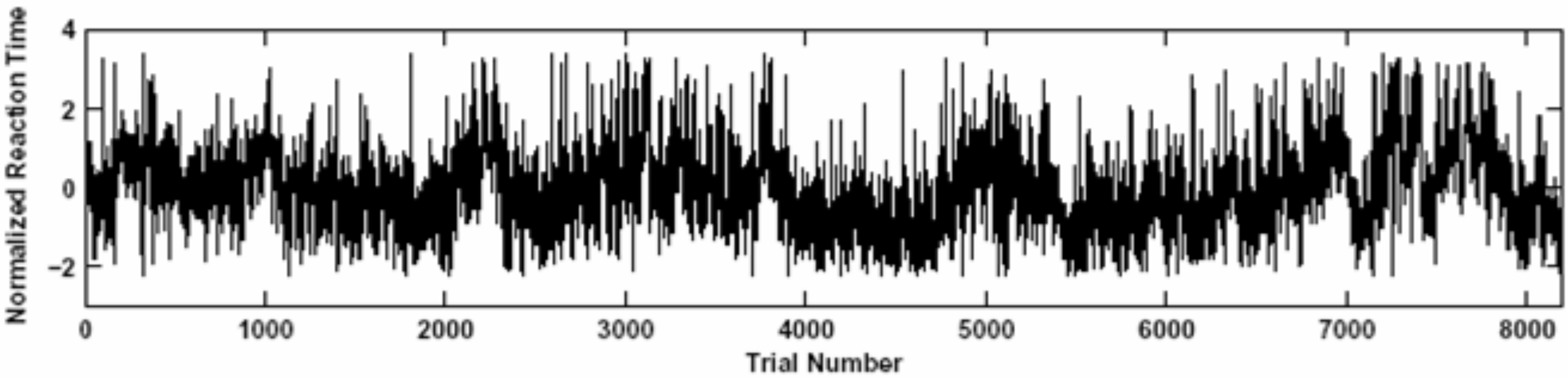
“Statistics”: More data = more variance



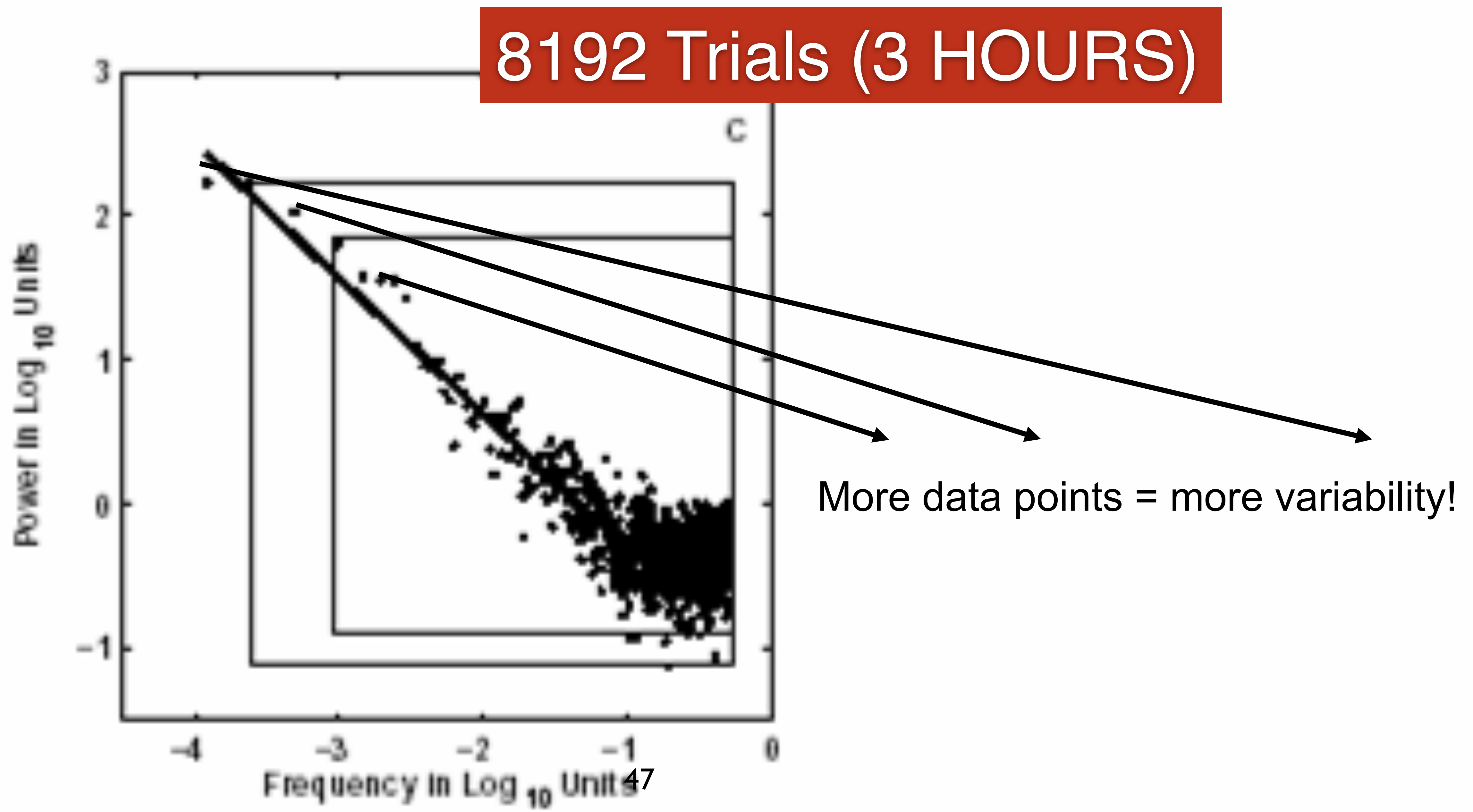








Normalized Reaction Time
4
2
0
−2
0
1000
2000
3000
4000
5000
6000
7000
8000
Trial Number



8192 Trials (3 HOURS)
C
3
2
1
0
−1
Power in Log 10 Units
−4
−3
−2
−1
0
Frequency in Log 10 Units
More data points = more variability!

Dynamics of Complex Systems

Scaling phenomena:

Applications

f.hasselman@bsi.ru.nl

Behavioural Science Institute
Radboud University Nijmegen

Scaling exponents reveal properties of data generating processes

Sixth International Conference on Noise in Physical Systems

Proceedings of a conference held at the National Bureau of Standards, Gaithersburg, MD, April 6-10, 1981

FOREWORD

The study of fluctuations (or noise) in a physical system provides insights, not available by any other technique, into the microscopic dynamic behavior of that system. Besides being a source of information, noise can also be a source of irritation, in that it limits the performance of numerous devices. The study of noise is of prime importance for the testing of physical theories as well as for the development of improved physical measurements and improved performance of devices. Therefore, the Conference has as one of its goals an improved understanding of noise in devices and its influence on the error budget of a measurement. Indeed, progress in relieving or minimizing noise in some devices was reported (e.g., the relationship of "burst noise" to the metallurgical condition of the sample).

Strong emphasis was given in this Conference to new topics for which the noise spectra proved to be particularly helpful in characterizing the underlying system dynamics. Papers discussed, for example, the transition from periodic to chaotic behavior in chemical systems and turbulent fluid flow, entropy generation in the computer process, the existence and implications of quantum mechanical noise, and noise spectra occurring in electrochemical processes.

Judging from the number of contributions and the intensity of the discussions following their presentations, the topic of 1/f noise remains as a very interesting one. It has resisted most, if not all theoretical attempts to explain it. An invited paper by T. Musha gave even more evidence to its ubiquity in nature. One of the most interesting developments here has been the connection between 1/f noise and human comfort. Extending beyond the observation that noise exhibiting a 1/f spectrum is pleasing to the listener, clinical evidence now suggests that electronic alleviation of pain in humans is improved when the electrical shocks are given a 1/f component.

Scaling phenomena: Time scales

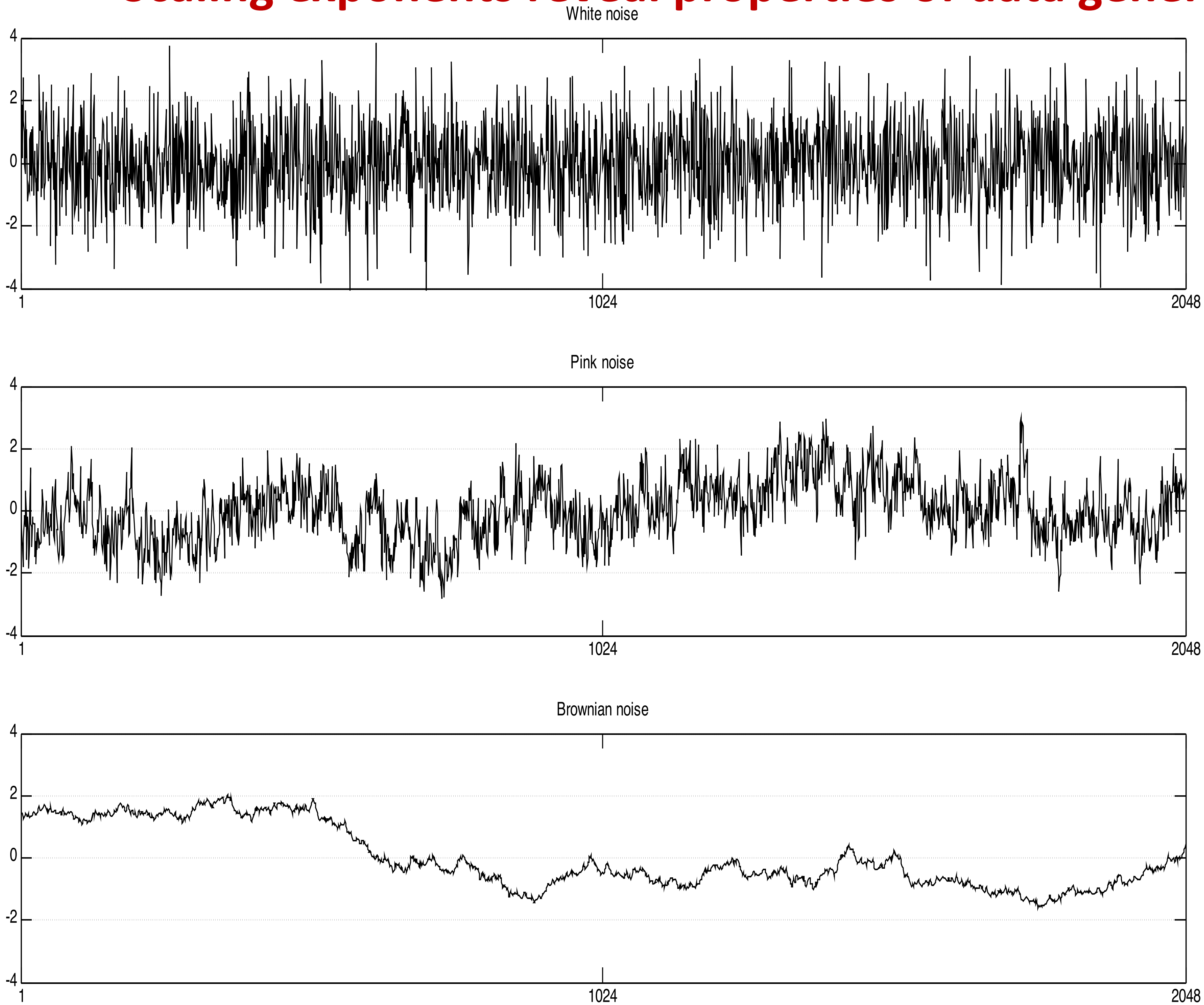
1/*f* Noise in Human Cognition

D. L. Gilden,* T. Thornton, M. W. Mallon

When a person attempts to produce from memory a given spatial or temporal interval, there is inevitably some error associated with the estimate. The time course of this error was measured in a series of experiments where subjects repeatedly attempted to replicate given target intervals. Sequences of the errors in both spatial and temporal replications were found to fluctuate as 1/*f* noises. 1/*f* noise is encountered in a wide variety of physical systems and is theorized to be a characteristic signature of complexity.

SCIENCE • VOL. 267 • 24 MARCH 1995

Scaling exponents reveal properties of data generating processes



White noise ~ 1.5

RANDOM
UNCORRELATED
UNCONSTRAINED

Pink noise ~ 1.2

Between:
order - random
constrained - unconstrained

Long-range dependence
Self-Organised Criticality

PERSISTENT
HIGHLY CORRELATED
CONSTRAINED

Random walk ~ 1.1

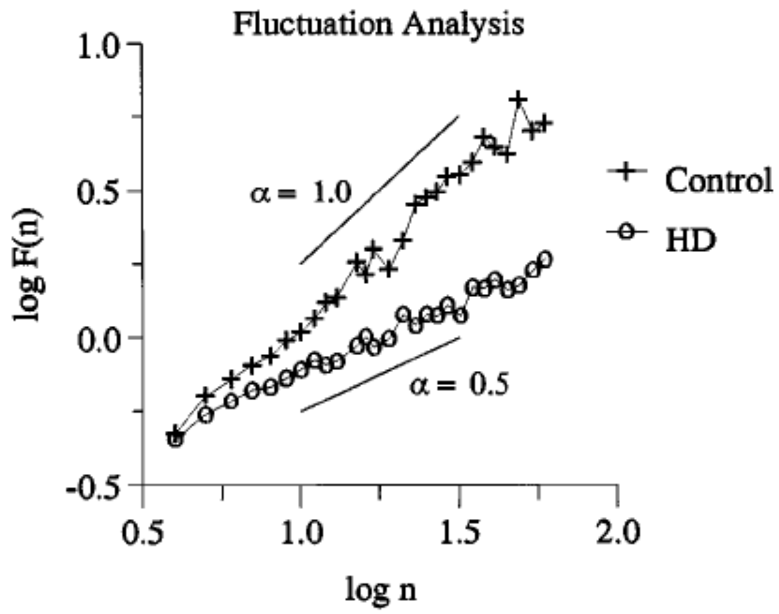
Line–like ~ 1

Fractal Physiology

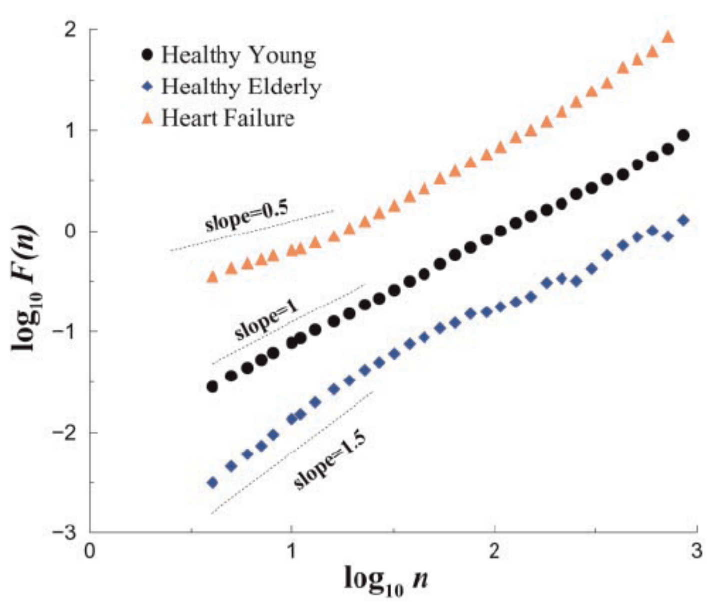
Multiplicative cascade / Multifractal formalism

Monofractal

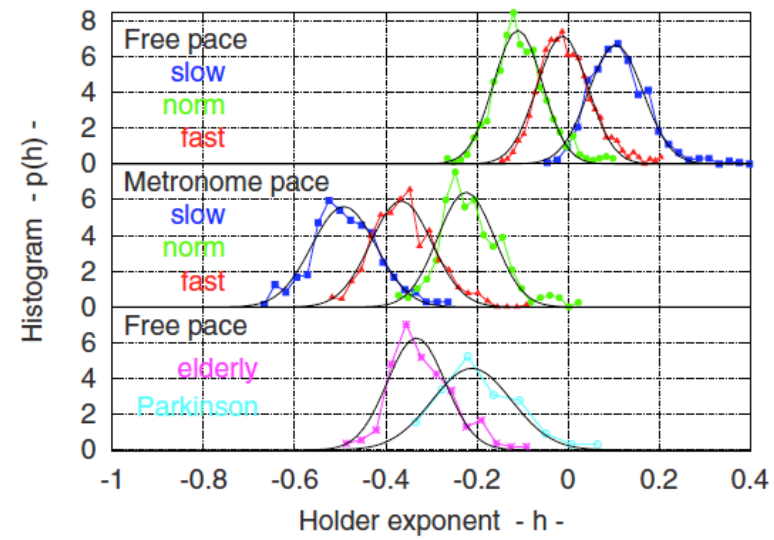
Stride intervals



Heart rate variability



Multifractal



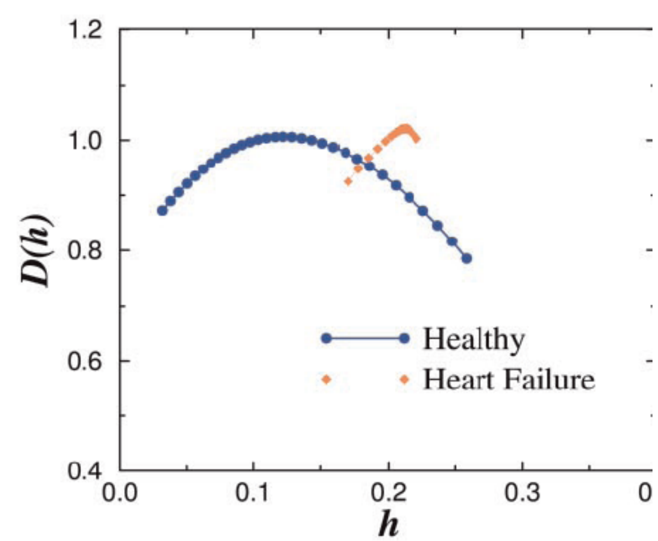
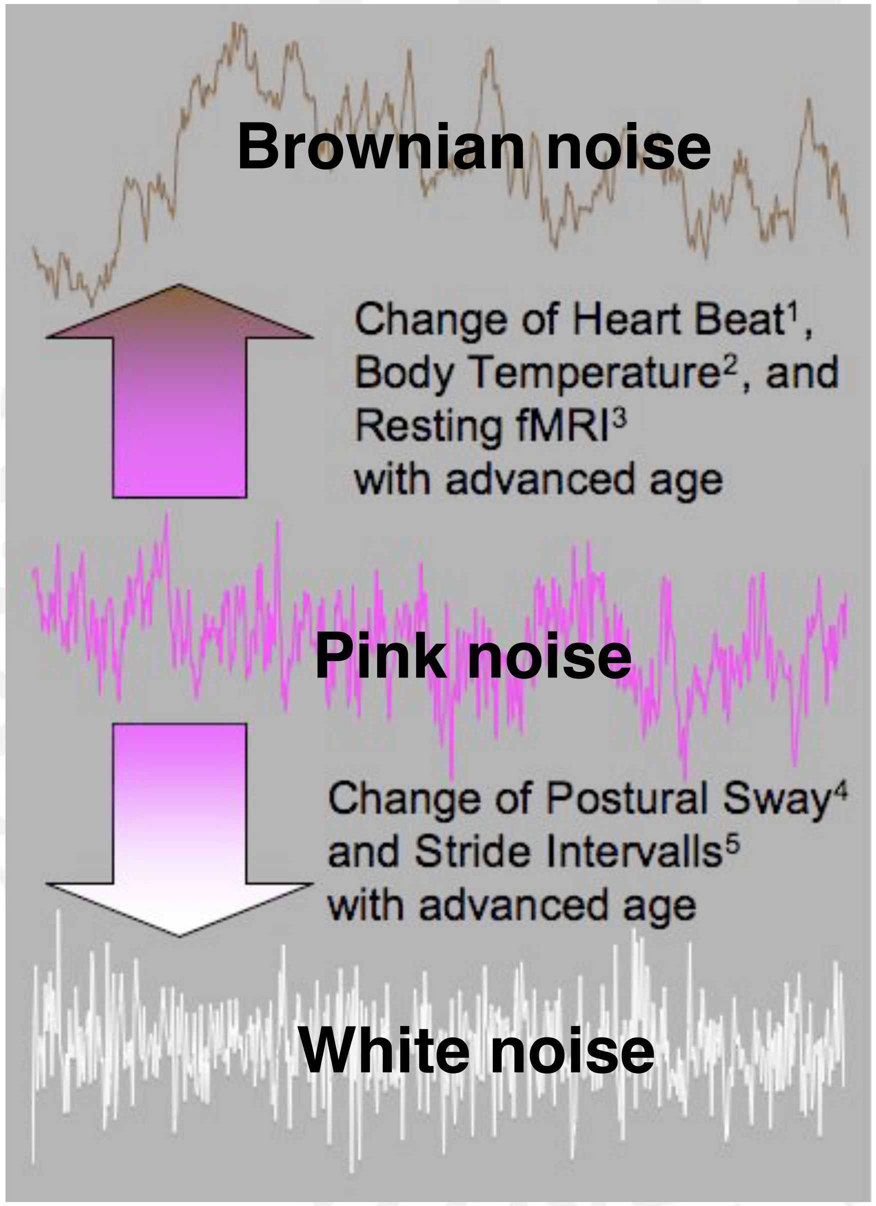


Fig. 7. Singularity spectra of heart rate signals in health and disease function *D(h)* measures the fractal dimension of the subset of the signal

Attraction to criticality



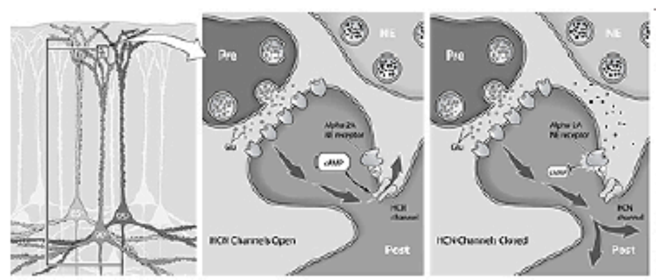
INTERVENTION: Almurad, Z. M., Roume, C., Blain, H., & Delignières, D. (2018). Complexity matching: Restoring the complexity of locomotion in older people through arm-in-arm walking. *Frontiers in physiology*, *9*, 1766.

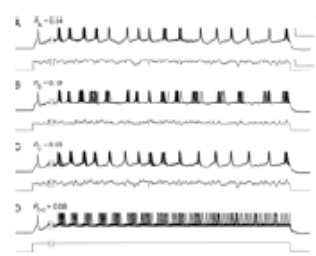
Fractal Neurophysiology

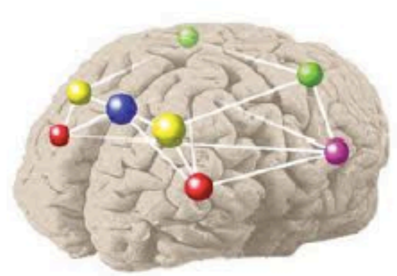
1/f noise in the Brain

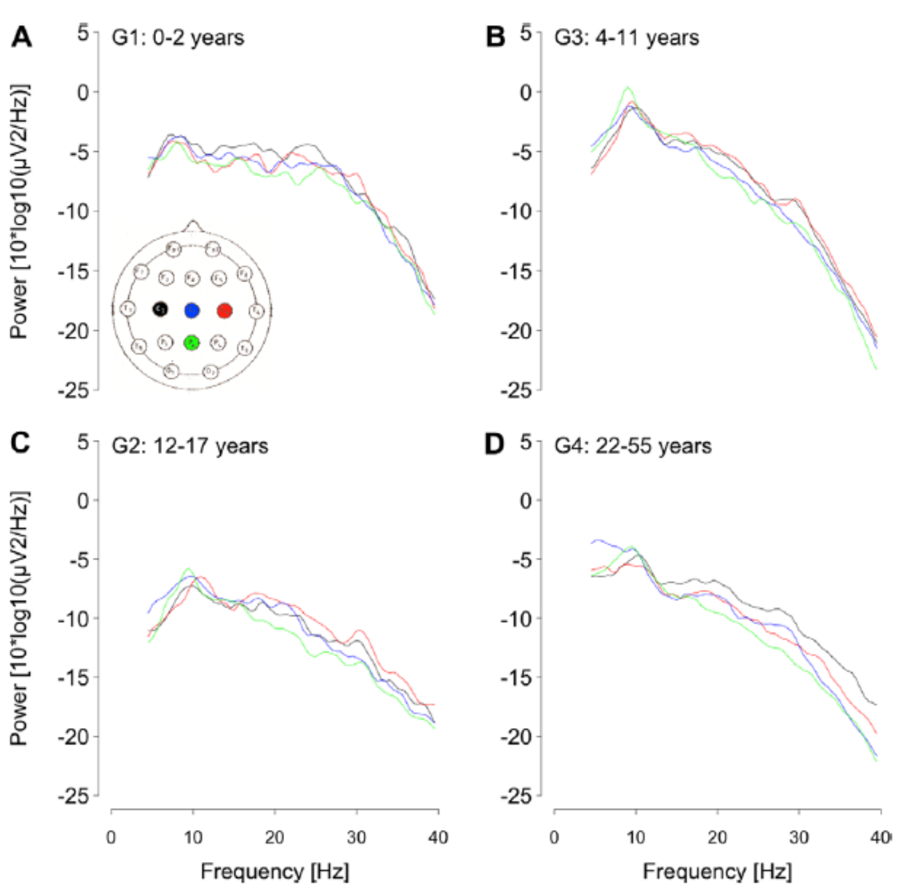
Wijnants, M. (2011)

- Ion Channels Opening and Closing Times
  - (Liebovitch & Krekora, 2002; Liebovitch & Shehadeh, 2005; Lowen , Cash, Poo, & Teich, 1997; Takeda, Sakata, & Matsuoka, 1999, Varanda, Liebovitch, Figueiroa, & Nogueira, 2000)
- Neural Spike Intervals
  - (Bhattacharya, Edwards, Mamelak, & Schuman, 2005; Giugliano, Darbon, Arsiero, Luescher, & Streit, 2004; Grüneis et al., 1993, West & Deering, 1994)
- Larger Scale Neural Assemblies
  - (Buzsàki, 2006; Bressler & Kelso, 2001; Freeman, Holmes, Burke, & Vanhatalo, 2003; Spasic, Kesic, Kalauzi, & Saponjic, 2010; Tognoli & Kelso, 2009; Varela, Lachaux, Rodriguez, & Martinerie, 2001; Werner, 2007)

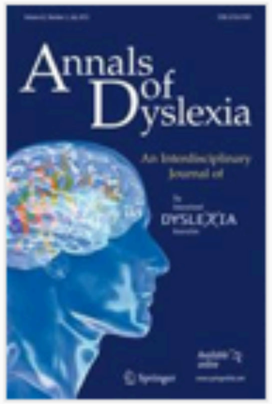








Berthouze, L., James, L. M., & Farmer, S. F. (2010). Human EEG shows long-range temporal correlations of oscillation amplitude in Theta, Alpha and Beta bands across a wide age range. Clinical neurophysiology, 121(8), 1187-97. doi: 10.1016/j.clinph.2010.02.163.



Annals of Dyslexia
July 2012, Volume 62, Issue 2, pp 100–119 | Cite as

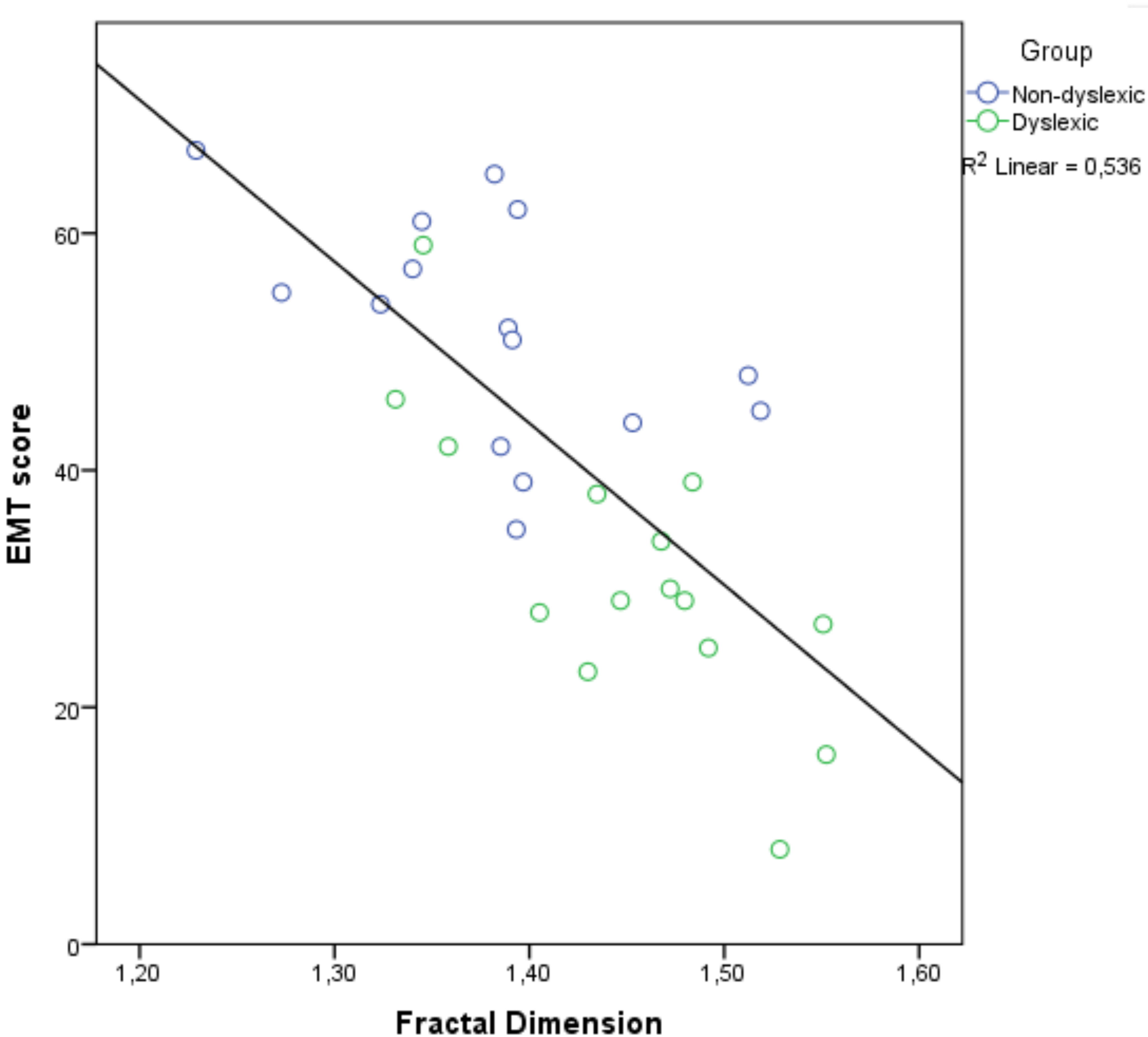
An interaction-dominant perspective on reading fluency and dyslexia

Authors | Authors and affiliations

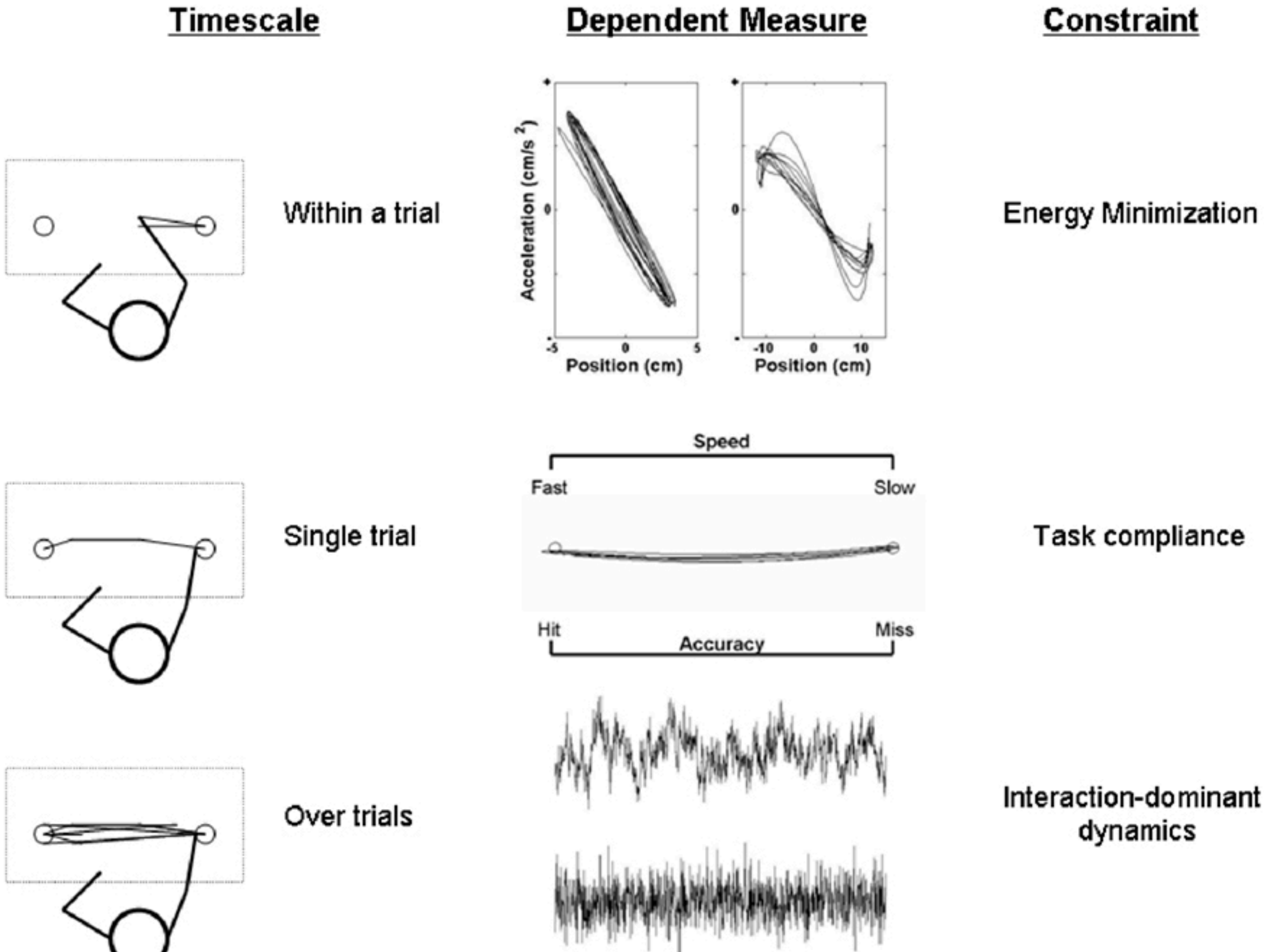
M. L. Wijnants, F. Hasselman, R. F. A. Cox, A. M. T. Bosman, G. Van Orden

Open Access | Article
First Online: 30 March 2012

- 560 single-syllable words
- Fast + accurate
- Record naming latency



Group
Non-dyslexic
Dyslexic
R2 Linear = 0,536
EMT score
0
20
40
60
1,20
1,30
1,40
1,50
1,60
Fractal Dimension



Wijnants, M., Cox, R., Hasselman, F., Bosman, A., & Van Orden, G. (2012). A trade-off study revealing nested timescales of constraint. *Frontiers in physiology*, *3*, 116.

Experimental Control over Scaling >> applications in sports science, e.g. cycling, rowing, swimming

- Hoos O., Boeselt T., Steiner M., Hottenrott K., Beneke R. (2014). Long-range correlations and complex regulation of pacing in long-distance road racing. Int. J. Sports Physiol. Perform. 9, 544–553. 10.1123/ijspp.2012-0334.
- Den Hartigh, R. J., Cox, R. F., Gernigon, C., Van Yperen, N. W., & Van Geert, P. L. (2015). Pink noise in rowing ergometer performance and the role of skill level. Motor control, 19(4), 355-369.
- Nourrit-Lucas, D., Tossa, A. O., Zélic, G., & Delignières, D. (2015). Learning, motor skill, and long-range correlations. Journal of motor behavior, 47(3), 182-189.
- Barbosa, T. M., Goh, W. X., Morais, J. E., Costa, M. J., & Pendergast, D. (2016). Comparison of classical kinematics, entropy, and fractal properties as measures of complexity of the motor system in swimming. Frontiers in psychology, 7, 1566.
- Den Hartigh, R. J., Marmelat, V., & Cox, R. F. (2018). Multiscale coordination between athletes: Complexity matching in ergometer rowing. Human movement science, 57, 434-441

Dynamics of Complex Systems

EXTRA:

Power law distributions

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Behavioural Science Institute
Radboud University Nijmegen

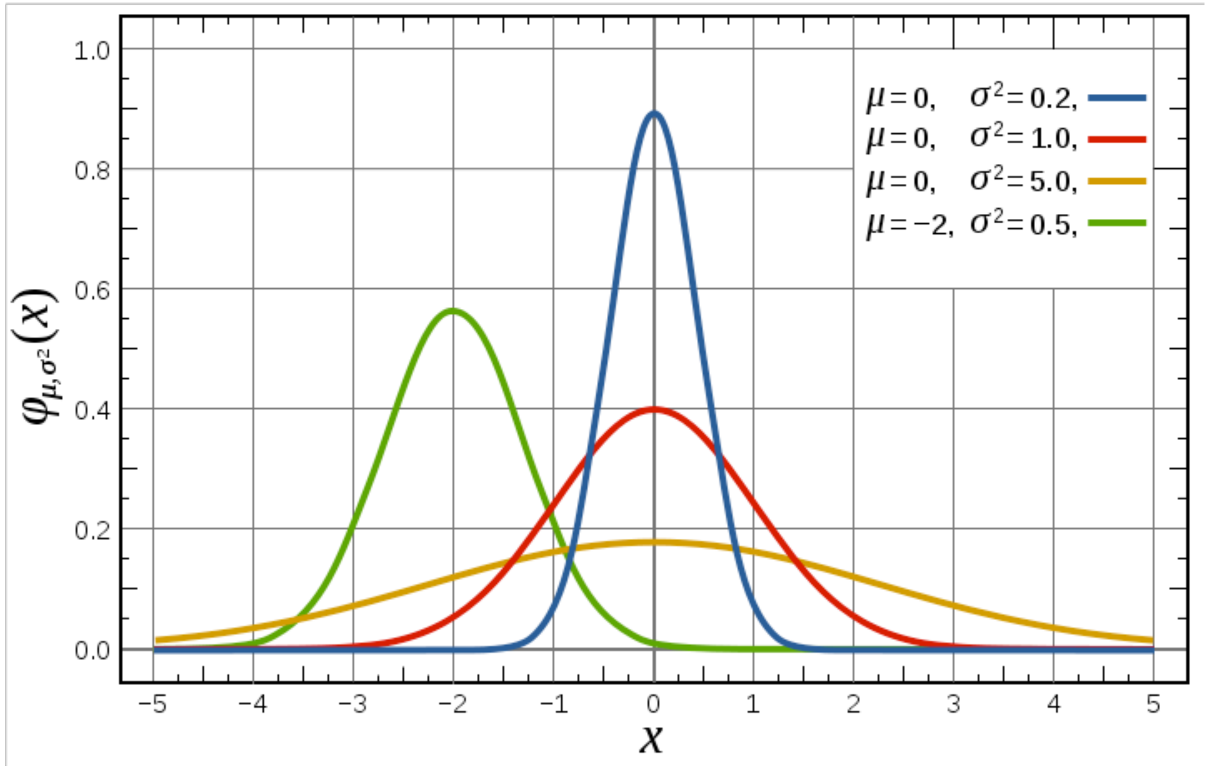
Normal / Gaussian

Probability Density Function

Two parameters:
Location (mean, **μ**), **Scale** (variance, **σ²**)

$$\frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

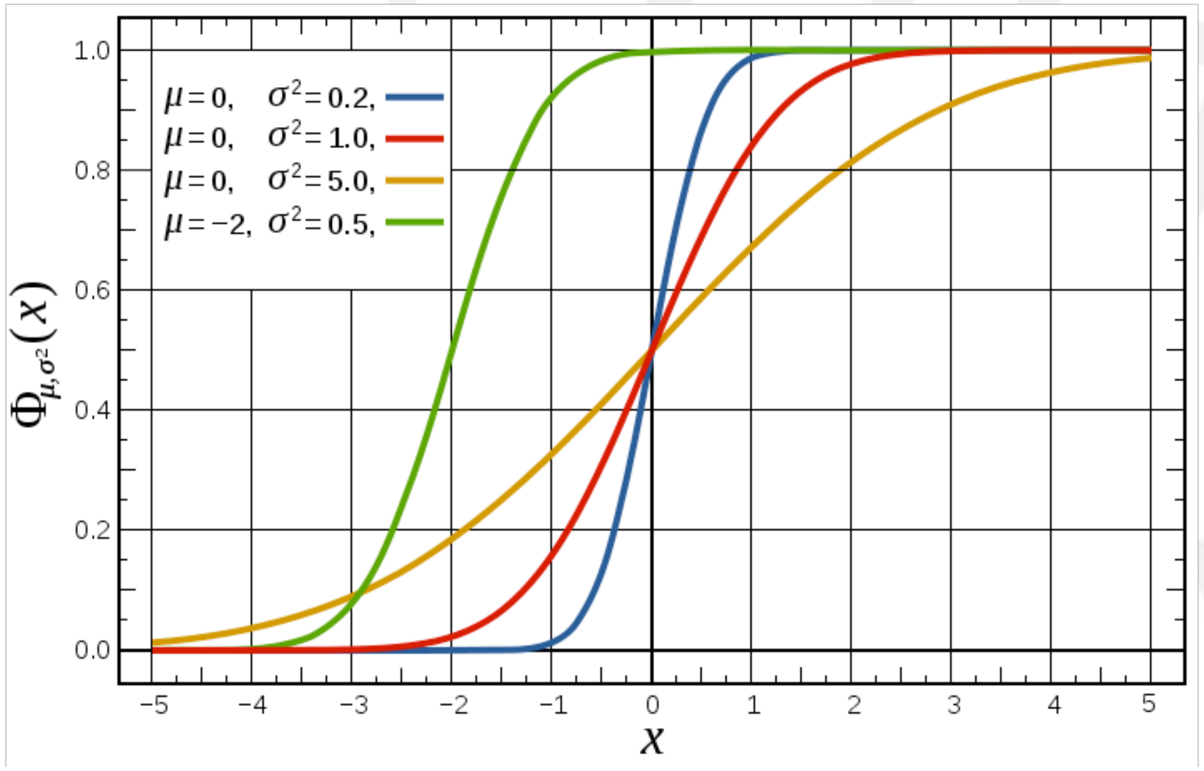
exponential family



Cumulative Distribution Function

Two parameters:
Location (mean, **μ**), **Scale** (variance, **σ²**)

$$\frac{1}{2}\left[1+\operatorname{erf}\left(\frac{x-\mu}{\sqrt{2\sigma^2}}\right)\right]$$



http://en.wikipedia.org/wiki/Normal_distribution

Pareto / Power Law

Probability Density Function

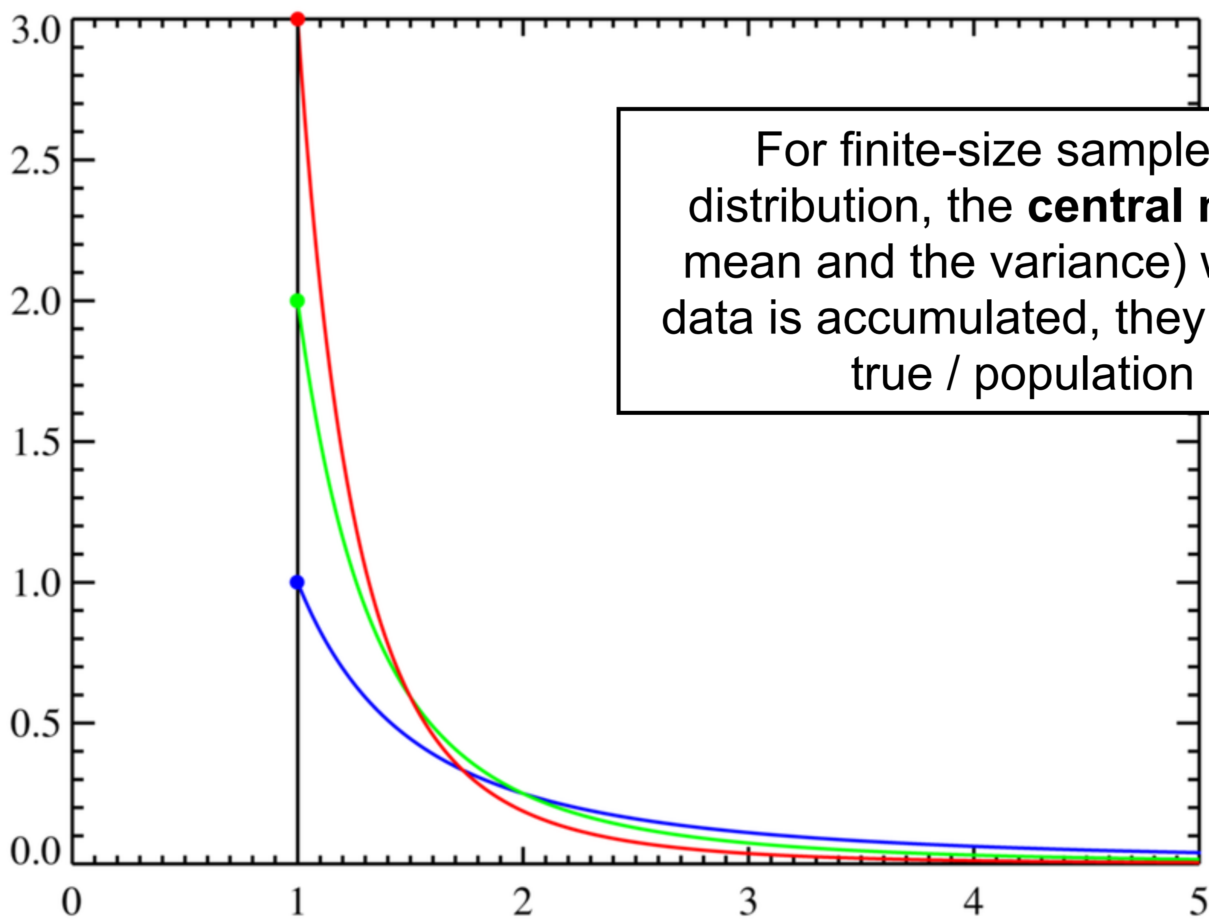
Two parameters:
Scale parameter (x_{min}),
Shape parameter (tail index: alpha)

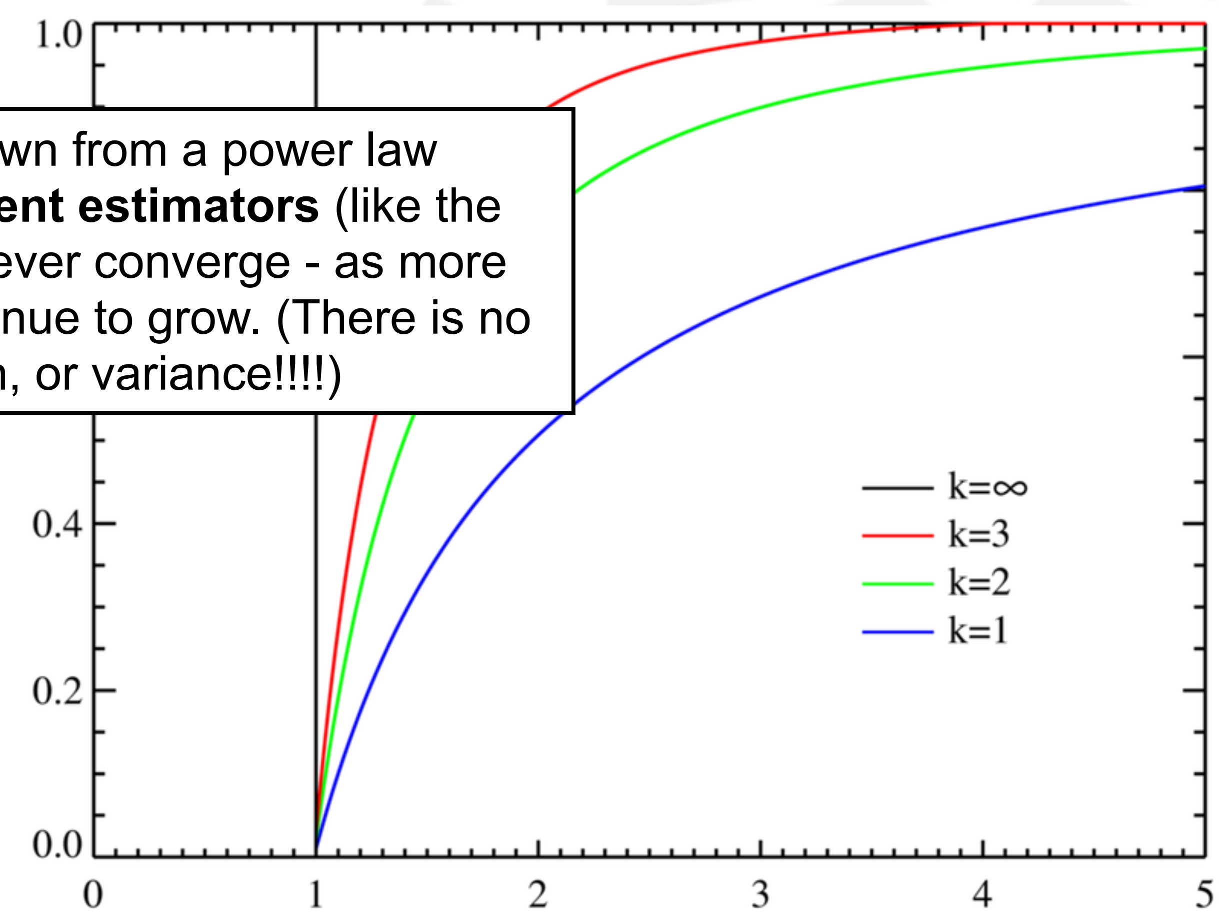
$$\frac{\alpha\, x_\mathrm{m}^\alpha}{x^{\alpha+1}} \text{ for } x \ge x_m$$

Cumulative Distribution Function

Two parameters:
Scale parameter (x_{min}),
Shape parameter (tail index: alpha)

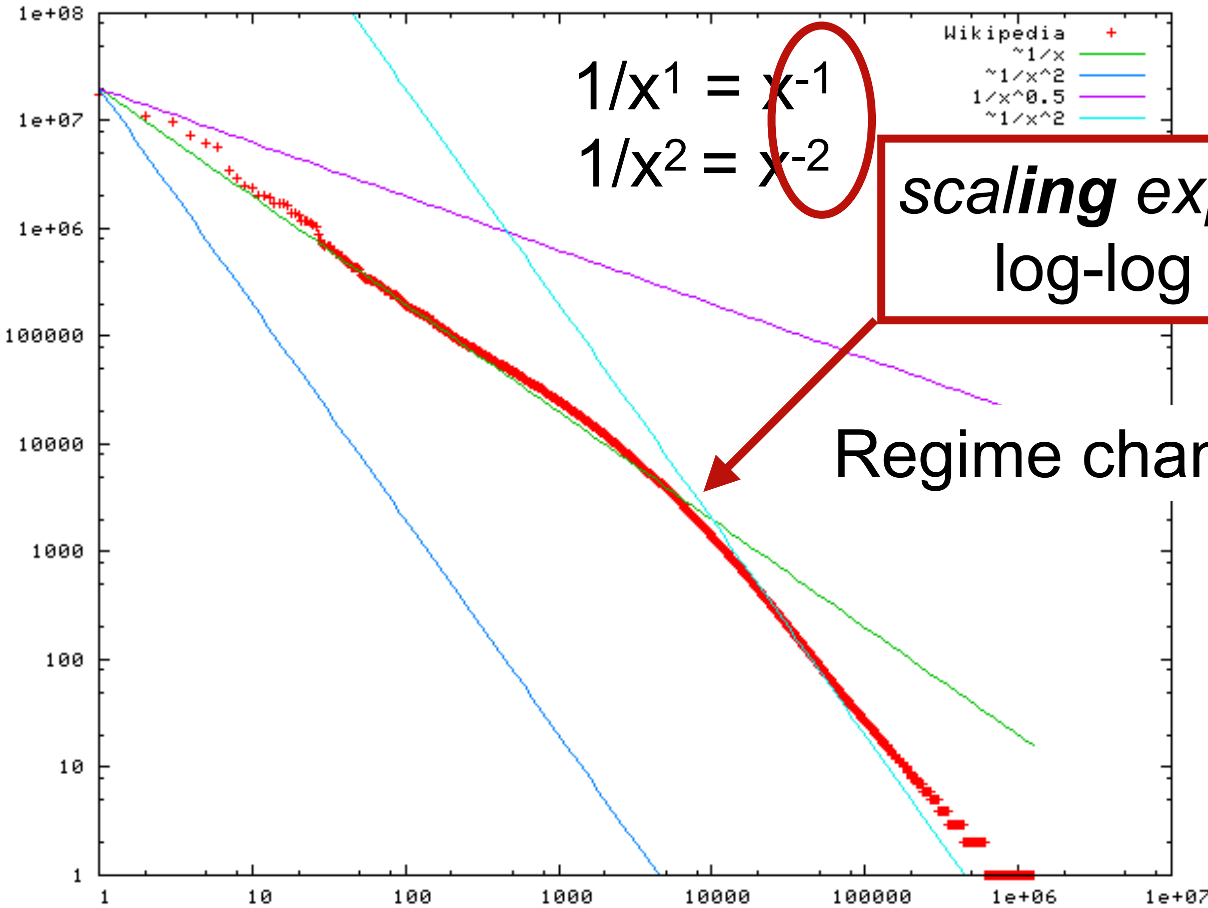
$$1-\left(\frac{x_\mathrm{m}}{x}\right)^\alpha \text{ for } x \ge x_m$$





For finite-size samples drawn from a power law distribution, the **central moment estimators** (like the mean and the variance) will never converge - as more data is accumulated, they continue to grow. (There is no true / population mean, or variance!!!!)

Mean and variance are undefined!!!!



$1/x^1 = x^{-1}$

$1/x^2 = x^{-2}$

scaling exponent = log-log slope

A plot of word rank in a frequency table vs. it's actual occurrence in Wikipedia (November 27, 2006)

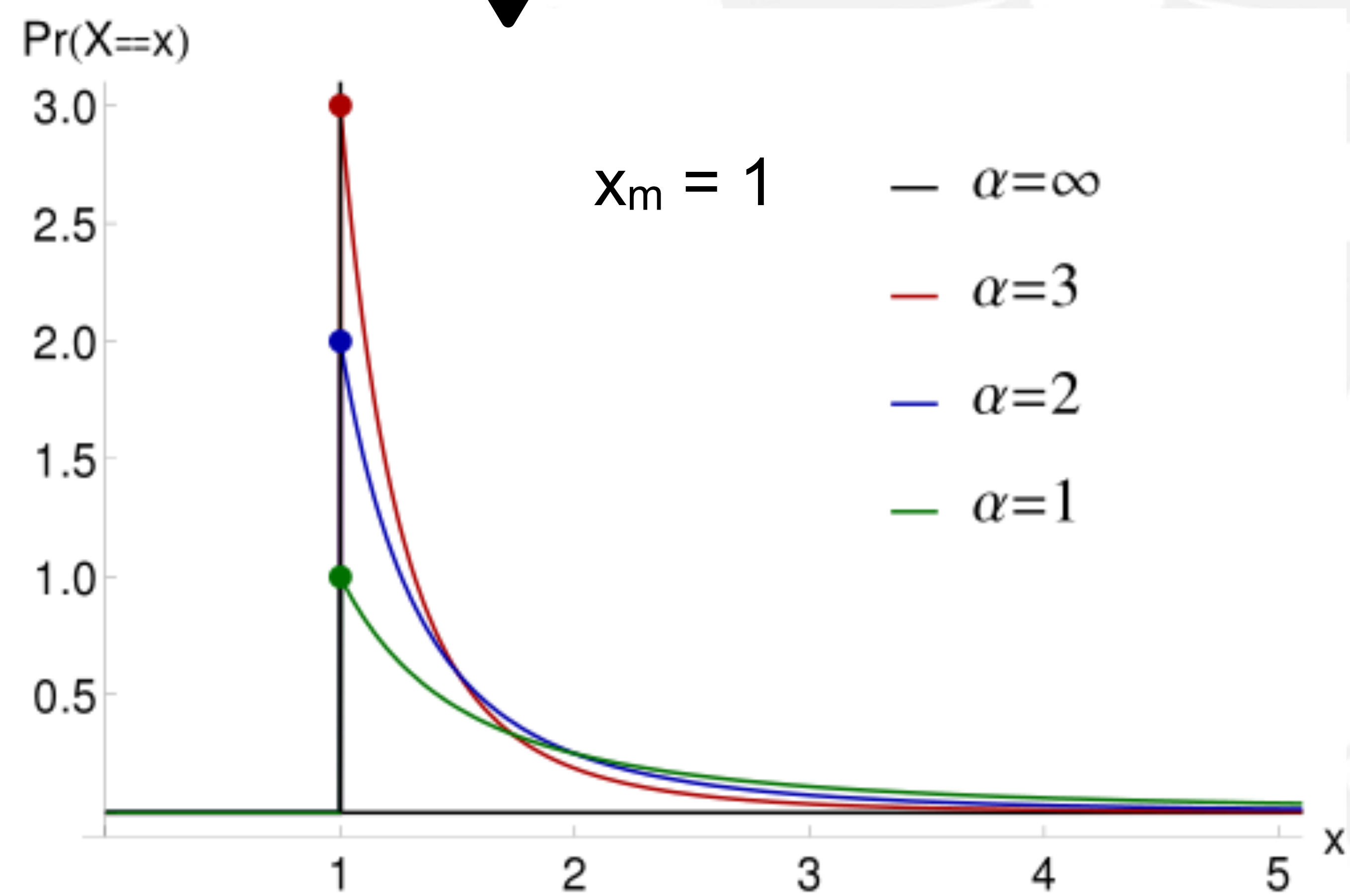
Pareto (type 1) distribution (continuous)

Zipfian distribution (discrete)

Power Law distribution

Regime change!

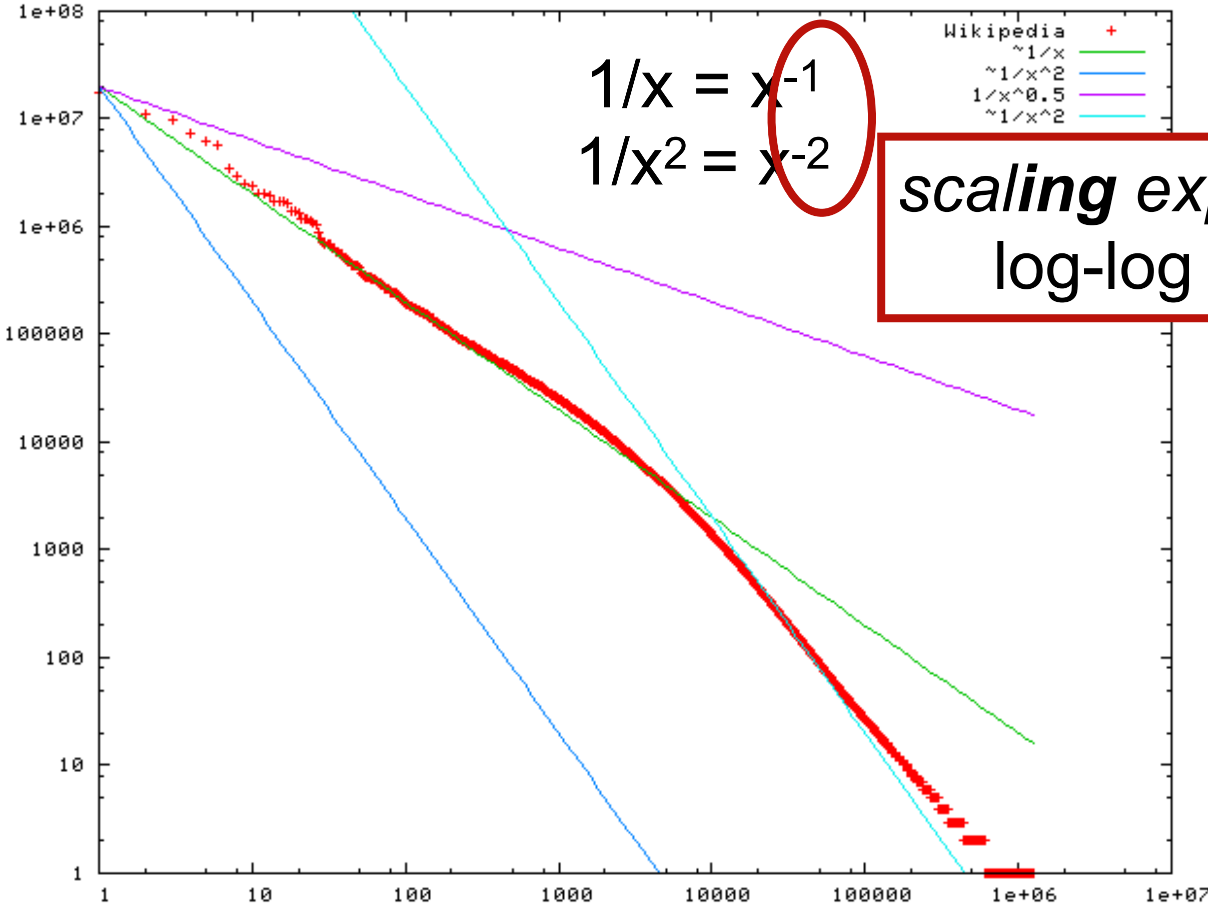
$$\frac{\alpha\, x_\mathrm{m}^\alpha}{x^{\alpha+1}} \text{ for } x \geq x_m$$



$x_m = 1$

Location and scale parameters (μ, σ), exist only under special conditions.

The *minimum scale value* $\boldsymbol{x_m}$ takes on the role of σ. There is no μ here, however, there is a *shape parameter* $\boldsymbol{\alpha}$ *(or* $\boldsymbol{k}$*)*



$1/x = x^{-1}$

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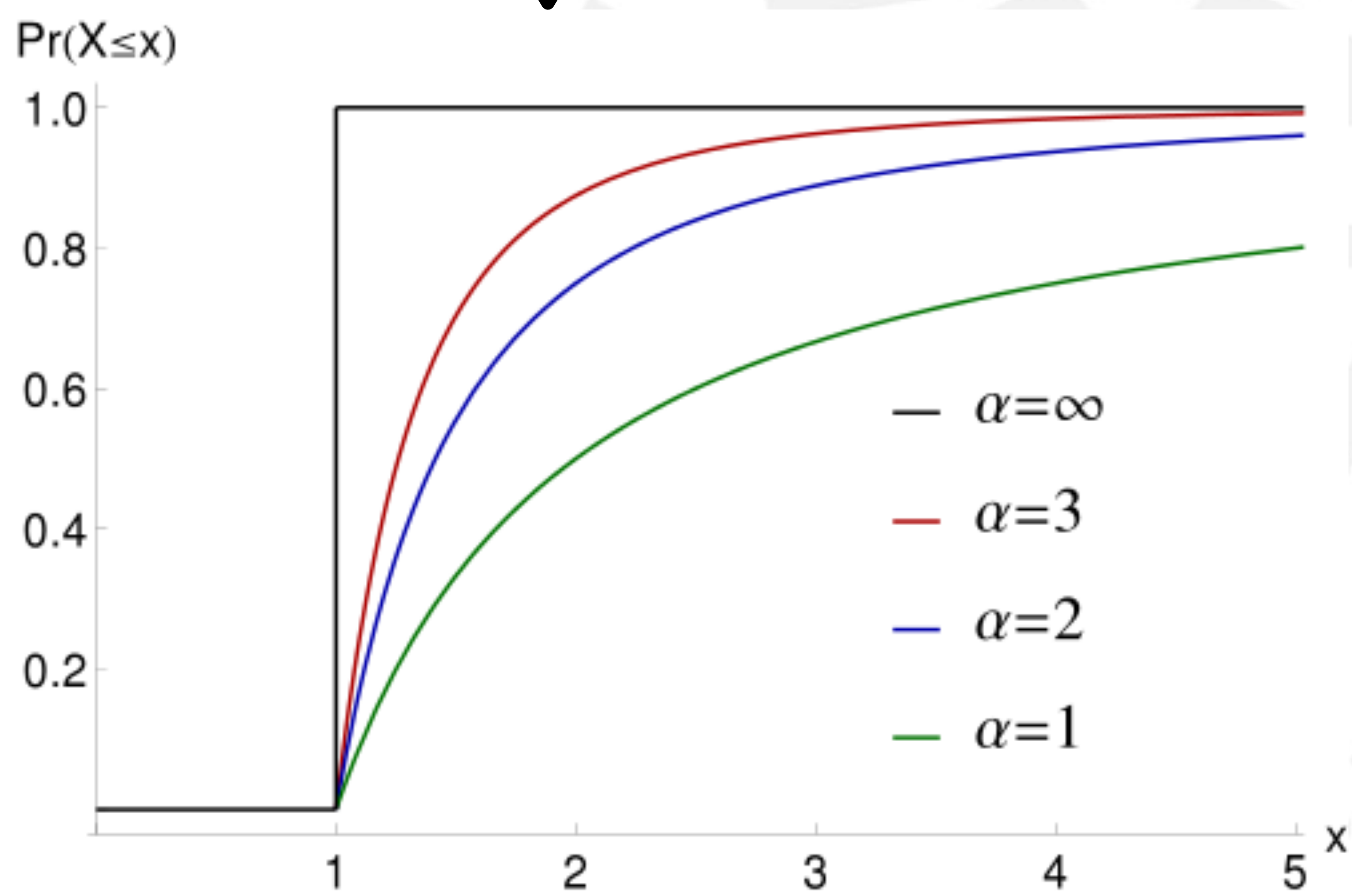
A plot of word rank in a frequency table vs. it's actual occurrence in Wikipedia (November 27, 2006)

<u>Pareto (type 1) distribution</u> (continuous)
<u>Zipfian distribution</u> (discrete)

Power Law distribution

$$1-\left(\frac{x_\mathrm{m}}{x}\right)^\alpha \text{ for } x \ge x_m$$



Pareto distributions are related to exponential growth:
If Y is exponentially growing at *rate* $\boldsymbol{\alpha}$,
then $\mathbf{x_m * e^Y}$ is Pareto distributed with *shape* $\boldsymbol{\alpha}$,
looks familiar:

$$\boxed{Y(t) = Y_0 \cdot e^{-\alpha \cdot t}}$$

$$\boxed{Y(t) = 1 - (1 - Y_0)\cdot e^{-\alpha \cdot t}}$$