

Time series analysis of flow reversals

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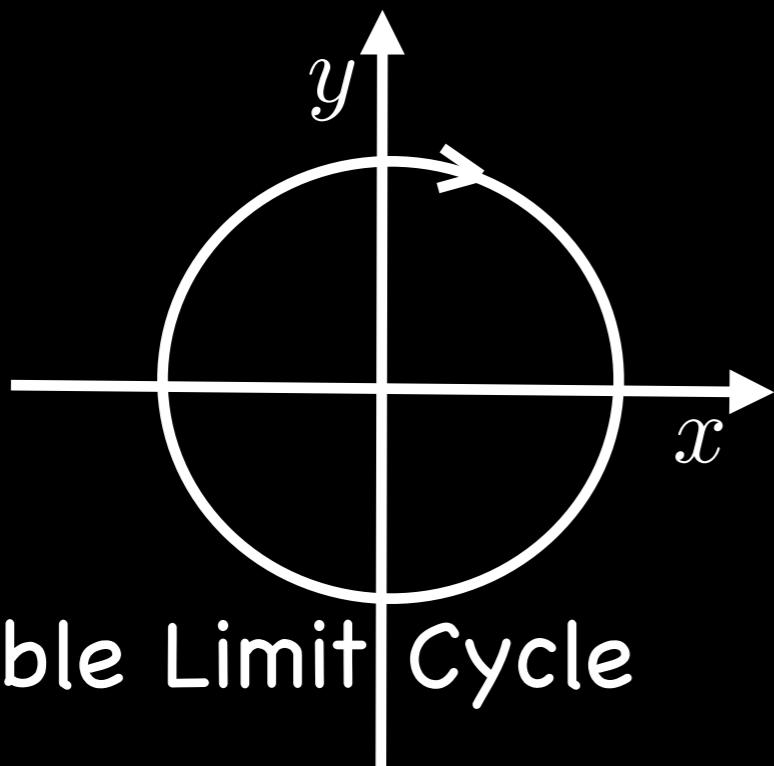
(Department of Mechanical Engineering, Indian Institute of Technology Kanpur).

Reconstruction: The Idea

$$\dot{r} = r(1 - r^2); \dot{\theta} = -1$$

$$\Rightarrow (x(t), y(t)) = (\sin t, \cos t)$$

(Asymptotically)

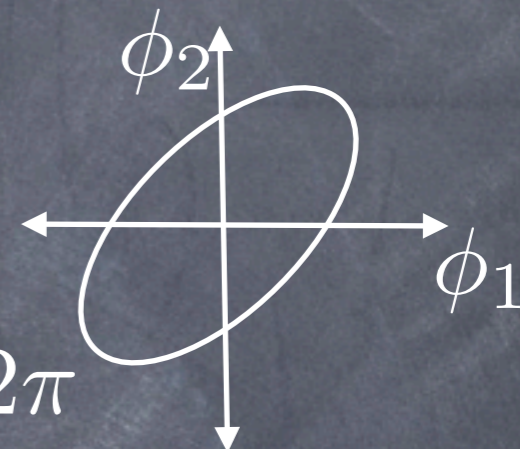


Stable Limit Cycle

$$\phi(x, y) = x(t) = \sin t = \phi_1$$

← ϕ_1 →
Embedding dimension (m)=1

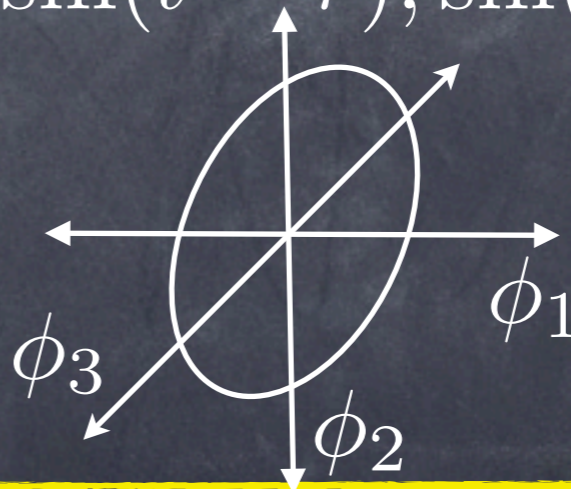
Form: $(\phi_1, \phi_2) \equiv (\sin t, \sin(t - \tau))$



Delay $\tau \neq \pi, 2\pi$

m=2

Construct: $(\phi_1, \phi_2, \phi_3) \equiv$
 $(\sin t, \sin(t - \tau), \sin(t - 2\tau))$



m=3

$\tau = ?$
 $m = ?$



Reconstruction: Embedding Dimension

Theorem 1. Let M be a compact manifold of dimension m . For pairs (φ, y) , $\varphi: M \rightarrow M$ a smooth diffeomorphism and $y: M \rightarrow \mathbb{R}$ a smooth function, it is a generic property that the map $\Phi_{(\varphi, y)}: M \rightarrow \mathbb{R}^{2m+1}$, defined by

$$\Phi_{(\varphi, y)}(x) = (y(x), y(\varphi(x)), \dots, y(\varphi^{2m}(x)))$$

(Takens, 1981)

is an embedding; by "smooth" we mean at least C^2 .

Theorem 2.5 (Fractal Delay Embedding Prevalence Theorem). Let Φ be a flow on an open subset U of R^k , and let A be a compact subset of U of box-counting dimension d . Let $n > 2d$ be an integer, and let $T > 0$. Assume that A contains at most a finite number of equilibria, no periodic orbits of Φ of period T or $2T$, at most finitely many periodic orbits of period $3T, 4T, \dots, nT$, and that the linearizations of those periodic orbits have distinct eigenvalues. Then for almost every smooth function h on U , the delay coordinate map $F(h, \Phi, T): U \rightarrow R^n$ is:

1. One-to-one on A .
2. An immersion on each compact subset C of a smooth manifold contained in A .

(Sauer, Yorke & Casdagli, 1991)

$m > 2D_b$
Sufficient
Condition

Reconstruction: Time Delay

Prescription for choosing delay:
look for either first zero of linear auto-correlation,

$$C_\tau \equiv \langle (\phi_1(t) - \langle \phi_1 \rangle)(\phi_1(t - \tau) - \langle \phi_1 \rangle) \rangle$$

or,

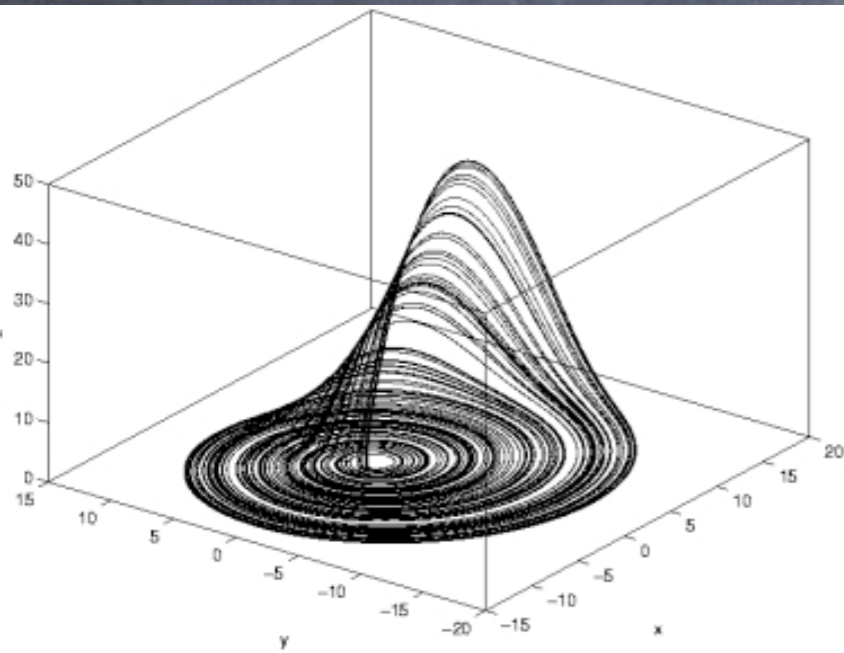
first minimum of the average mutual information,

$$I_\tau \equiv \sum_{\phi_1(t), \phi_1(t-\tau)} P(\phi_1(t), \phi_1(t - \tau)) \log_2 \left[\frac{P(\phi_1(t), \phi_1(t - \tau))}{P(\phi_1(t))P(\phi_1(t - \tau))} \right]$$

(Fraser & Swinney, 1986)

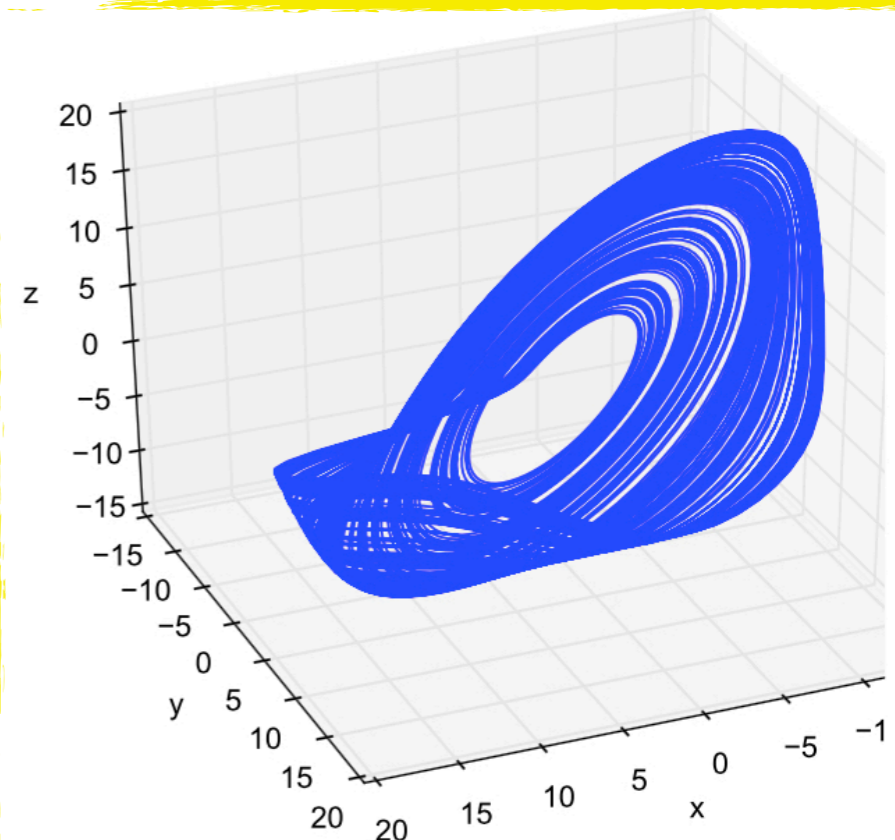
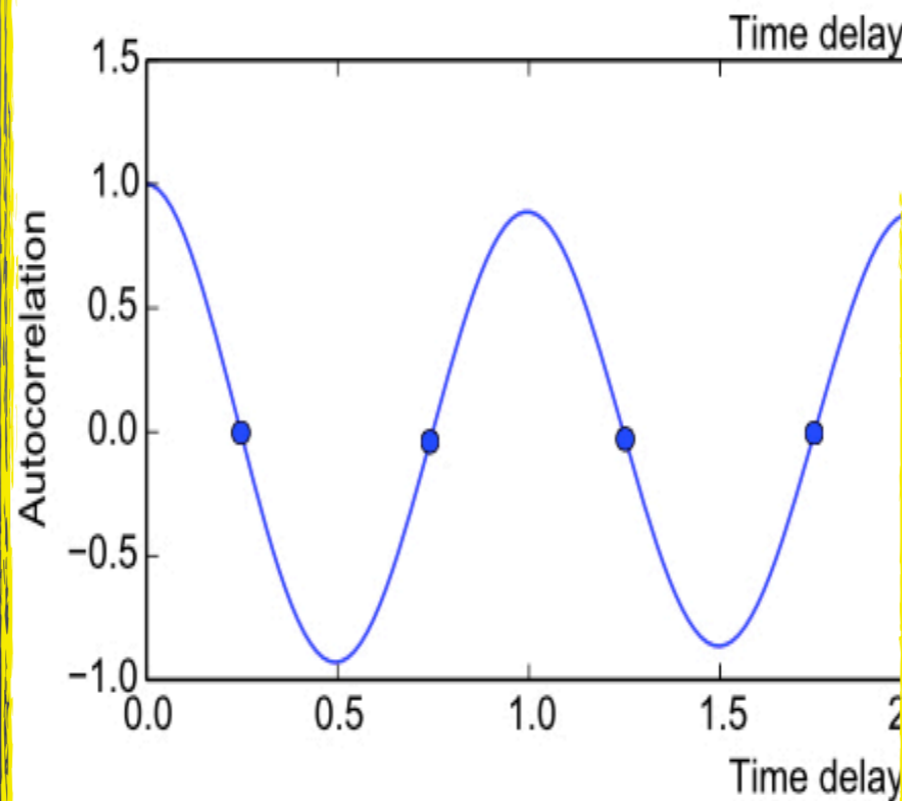
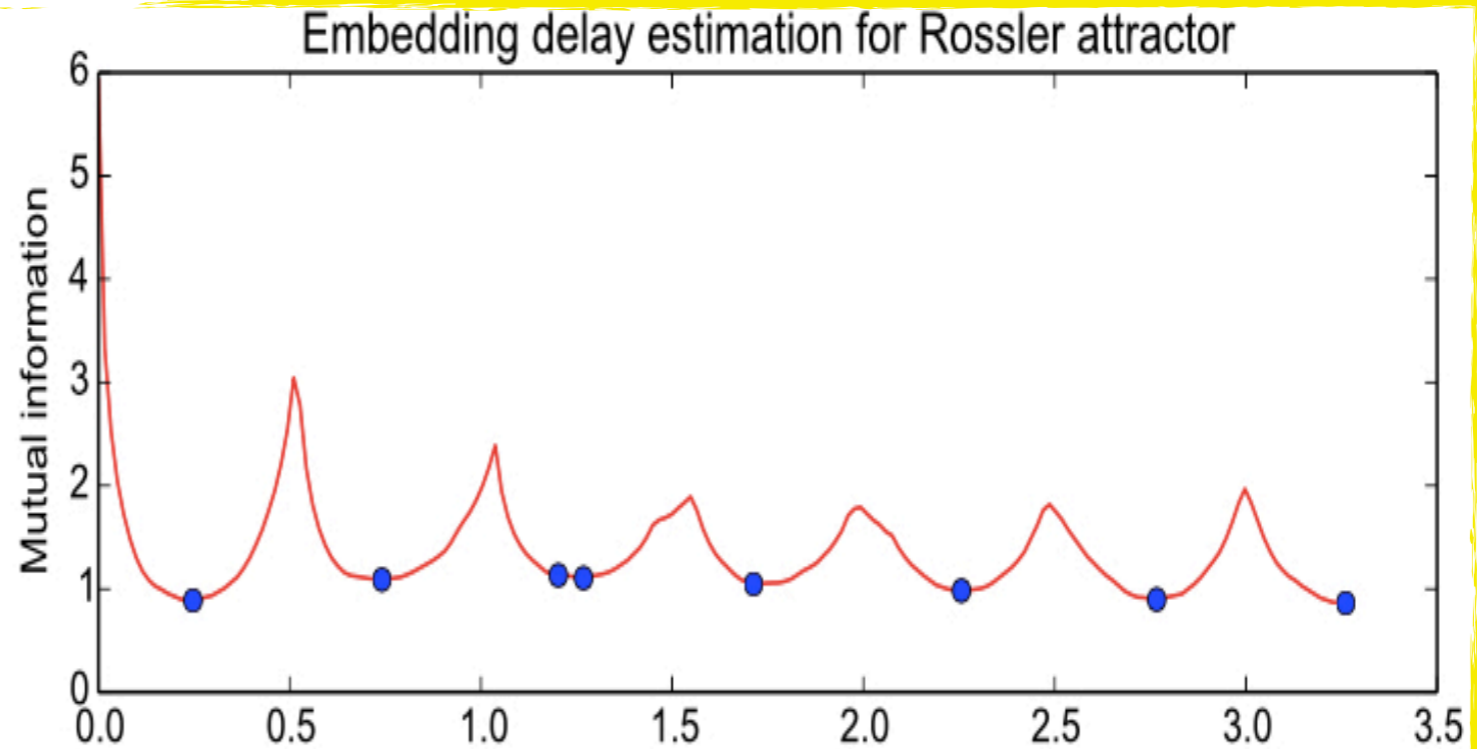
Reconstruction: Rössler Attractor

$$\begin{aligned}\dot{x} &= -y - z, \\ \dot{y} &= x + ay, \\ \dot{z} &= b + z(x - c)\end{aligned}$$



$$D_{KY} \approx 2.01$$

$$D_c \approx 1.99$$



Reconstruction: AFNN (Cao, 1997)

Scalar time-series and delay-reconstructed vector:

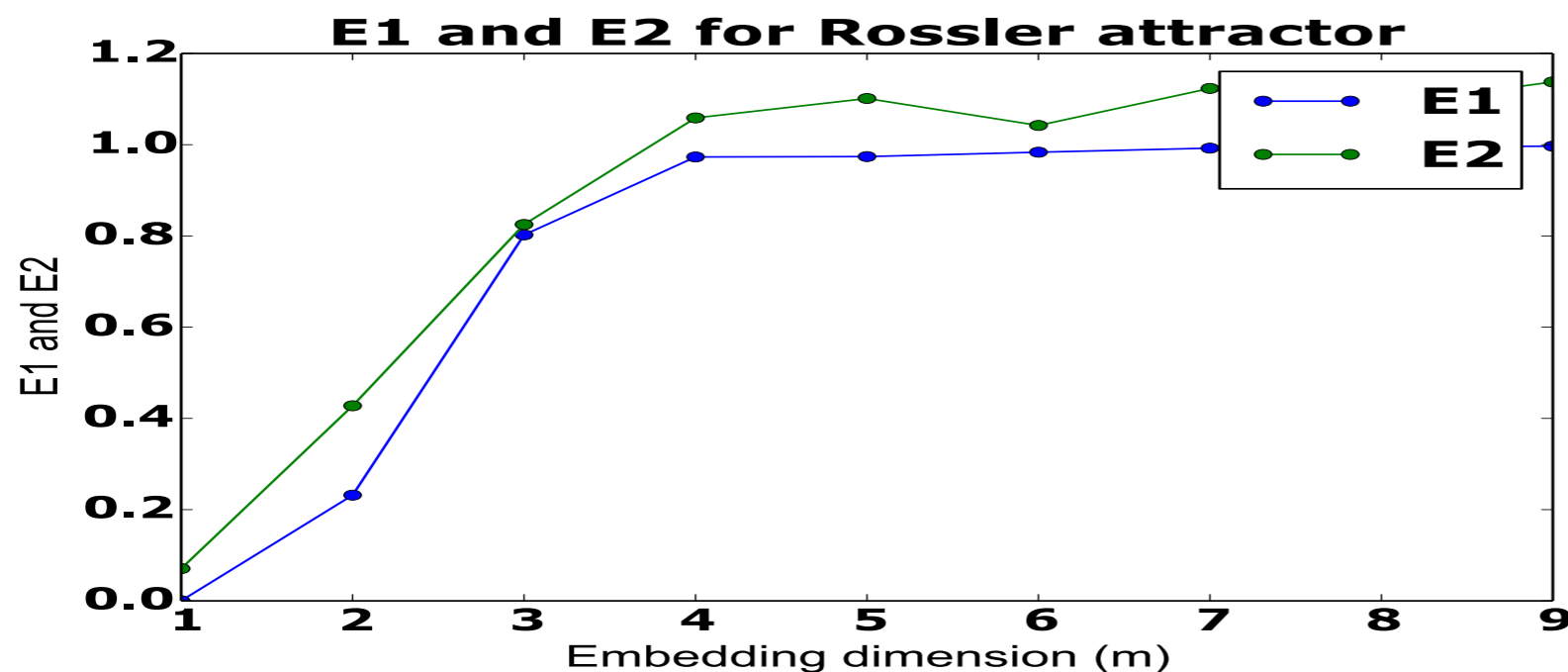
$$\mathbf{x} = (x_1, x_2, \dots, x_N); \mathbf{y}_i = (x_i, x_{i+\tau}, \dots, x_{i+(d-1)\tau})$$

Average magnifications in NN-distance and their ratios:

$$E(d) \equiv \frac{\sum_{i=1}^{N-d\tau} \frac{\|\mathbf{y}_i(d+1) - \mathbf{y}_{n(i,d)}(d+1)\|}{\|\mathbf{y}_i(d) - \mathbf{y}_{n(i,d)}(d)\|}}{N-d\tau}; E1(d) \equiv \frac{E(d+1)}{E(d)}$$

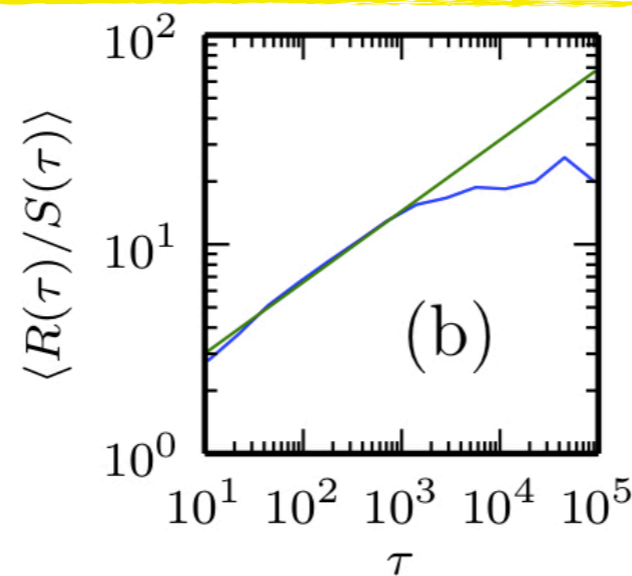
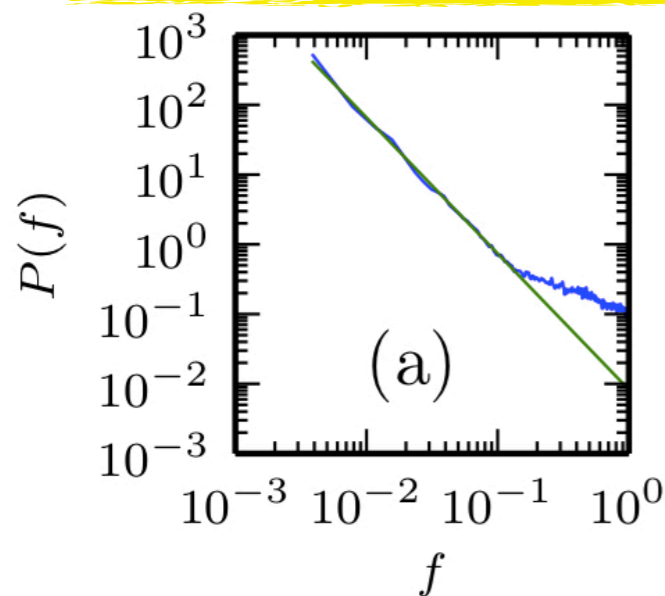
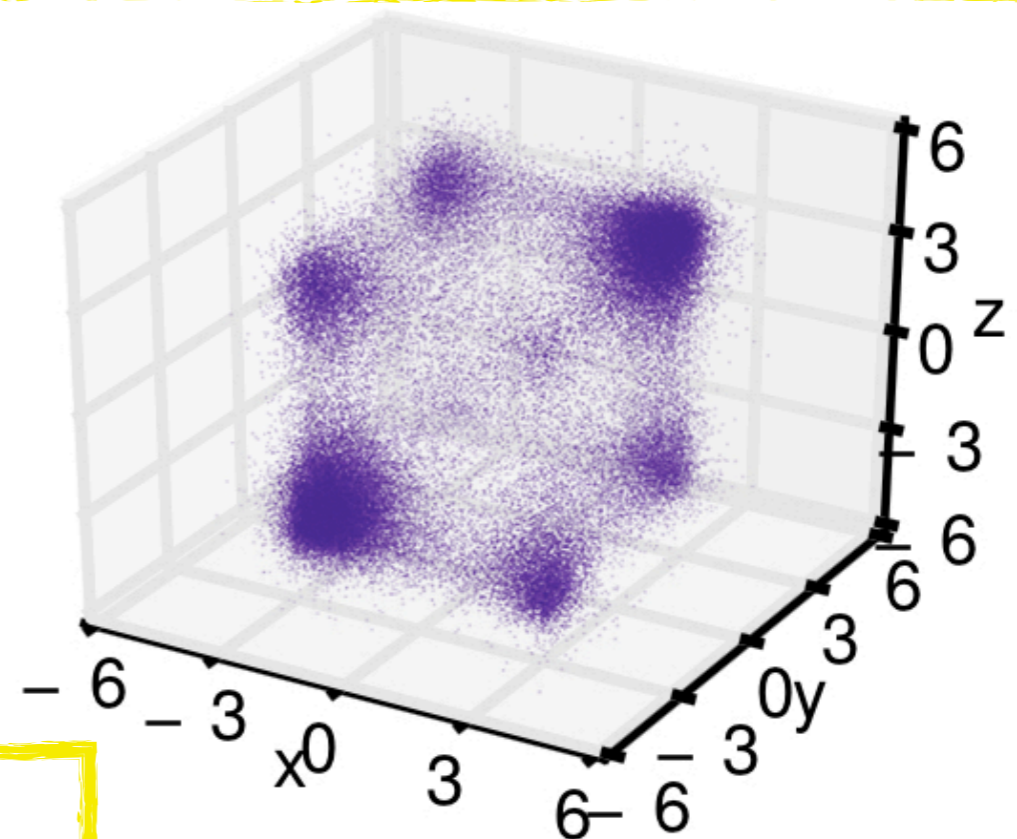
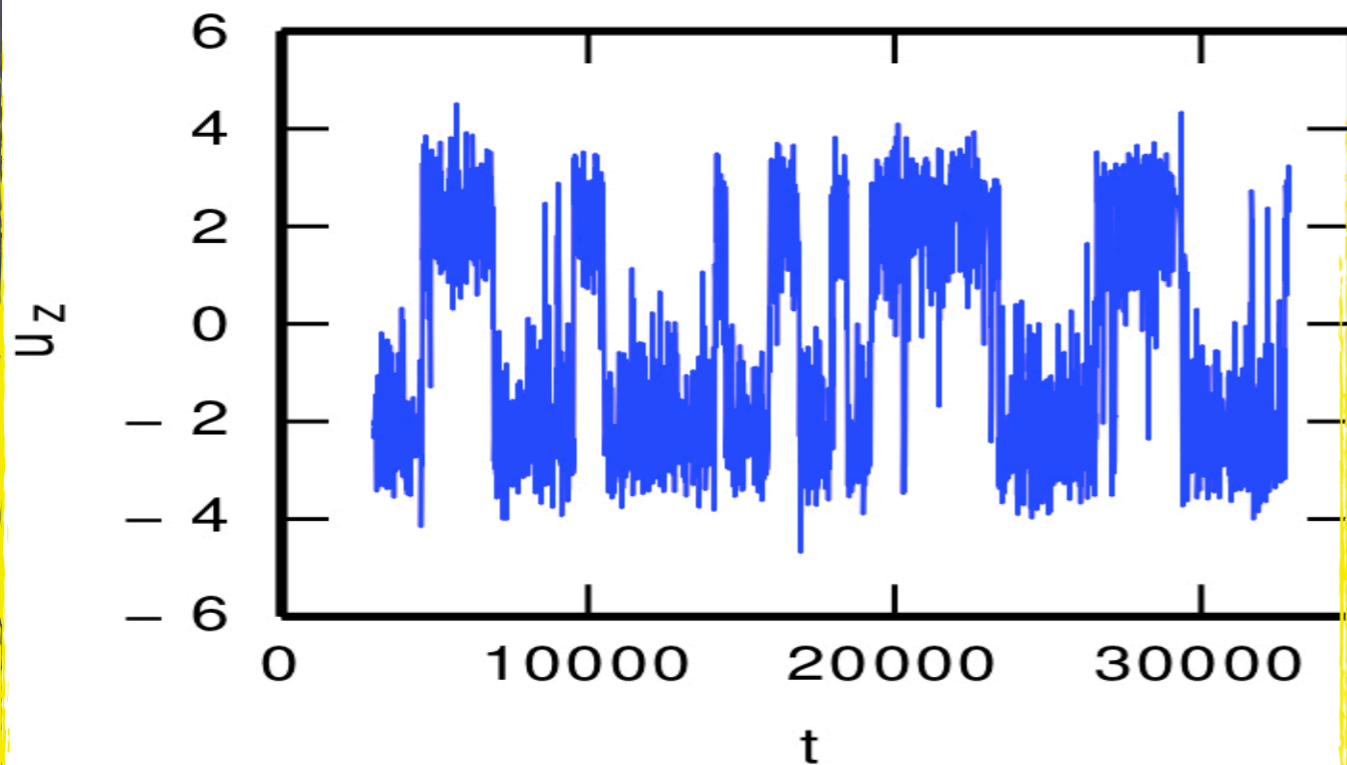
Average increases in NN-distance and their ratios:

$$E^*(d) \equiv \frac{\sum_{i=1}^{N-d\tau} |x_{i+d\tau} - x_{n(i,d)+d\tau}|}{N-d\tau}; E2(d) \equiv \frac{E^*(d+1)}{E^*(d)}$$



$$m = 4 \not\geq 2D_b$$

Reversal Time Series

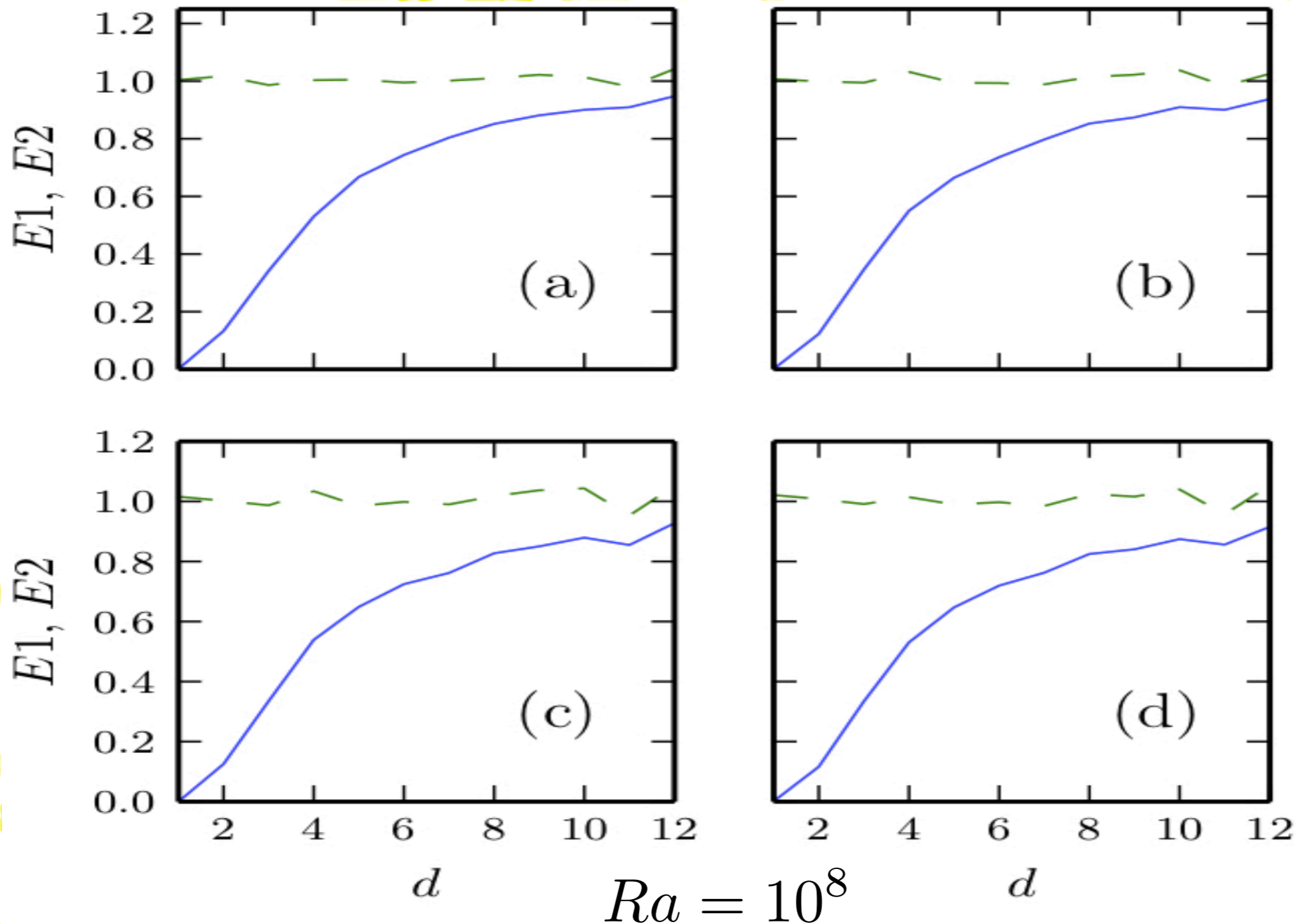


(a) Power spectrum ($\beta = 1.95$) and (b) R/S analysis for real space velocity u_z ($H = 0.34$).

Time Series
is
Anti-Persistent

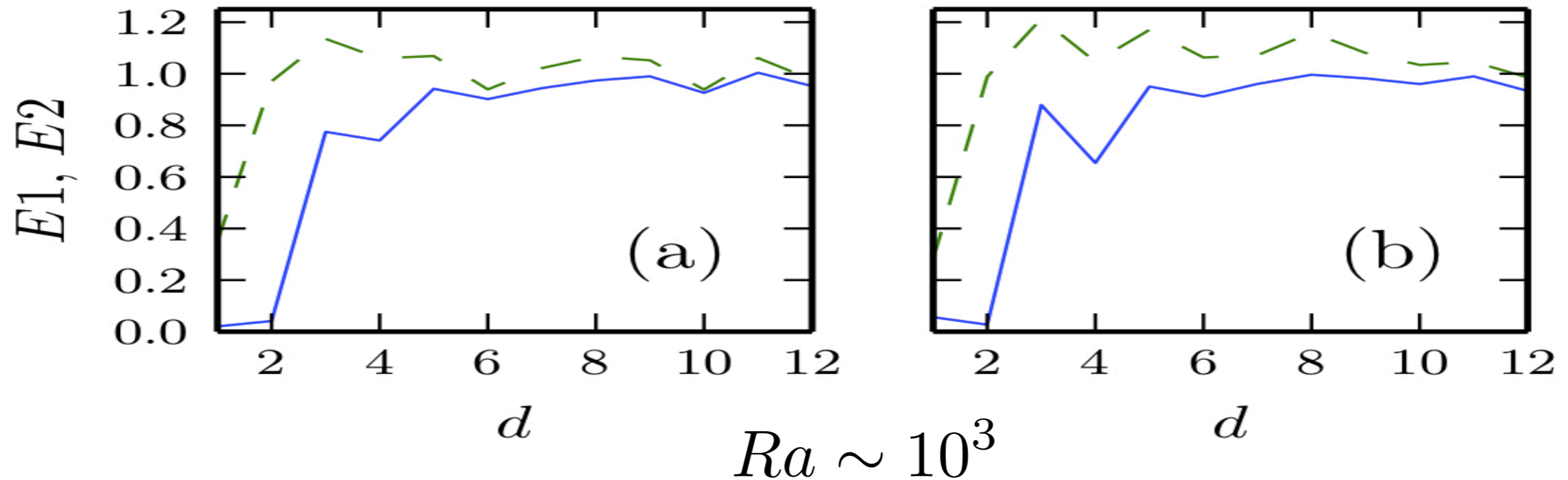
$$\therefore C(t) \sim 2^{2H-1} - 1$$

Reversal Time Series: AFNN



$E1$ and $E2$ curves. (a) u_z . (b) Fourier (1, 1) (c) Fourier (1, 3) (d) Fourier (1, 5).

Reversal Time Series: AFNN



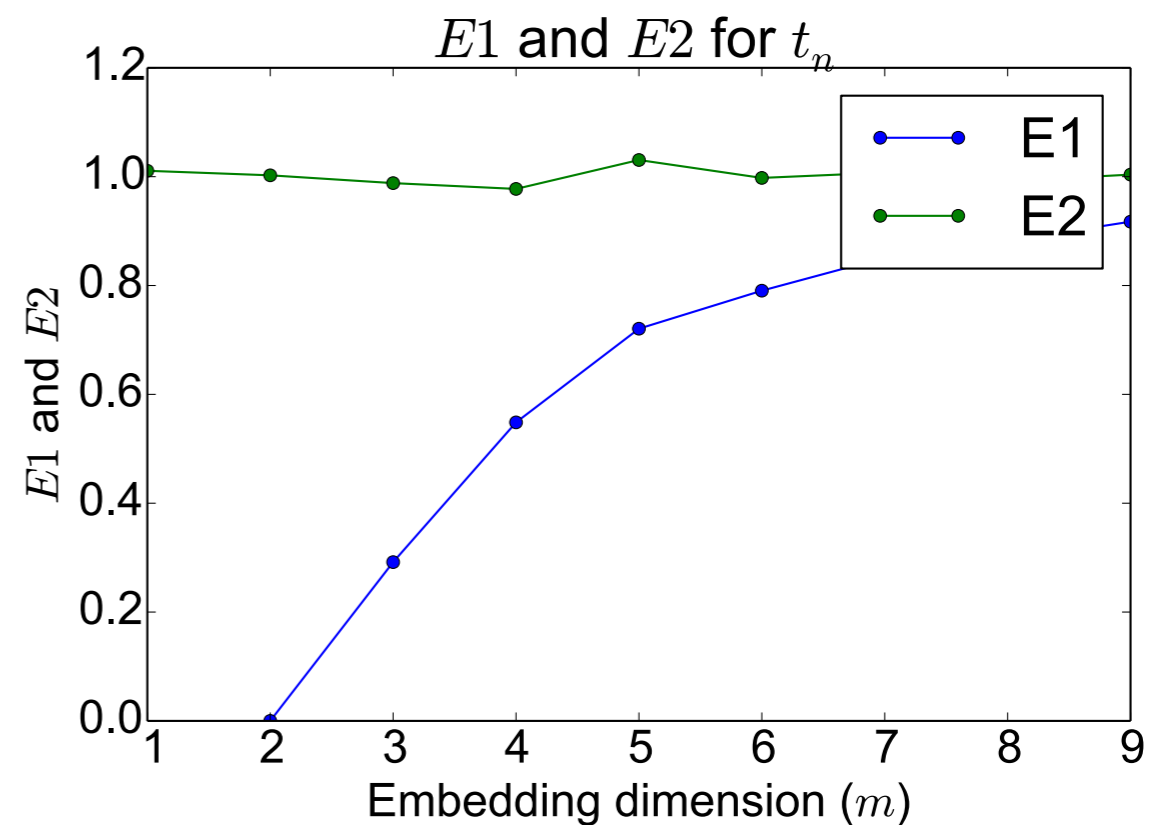
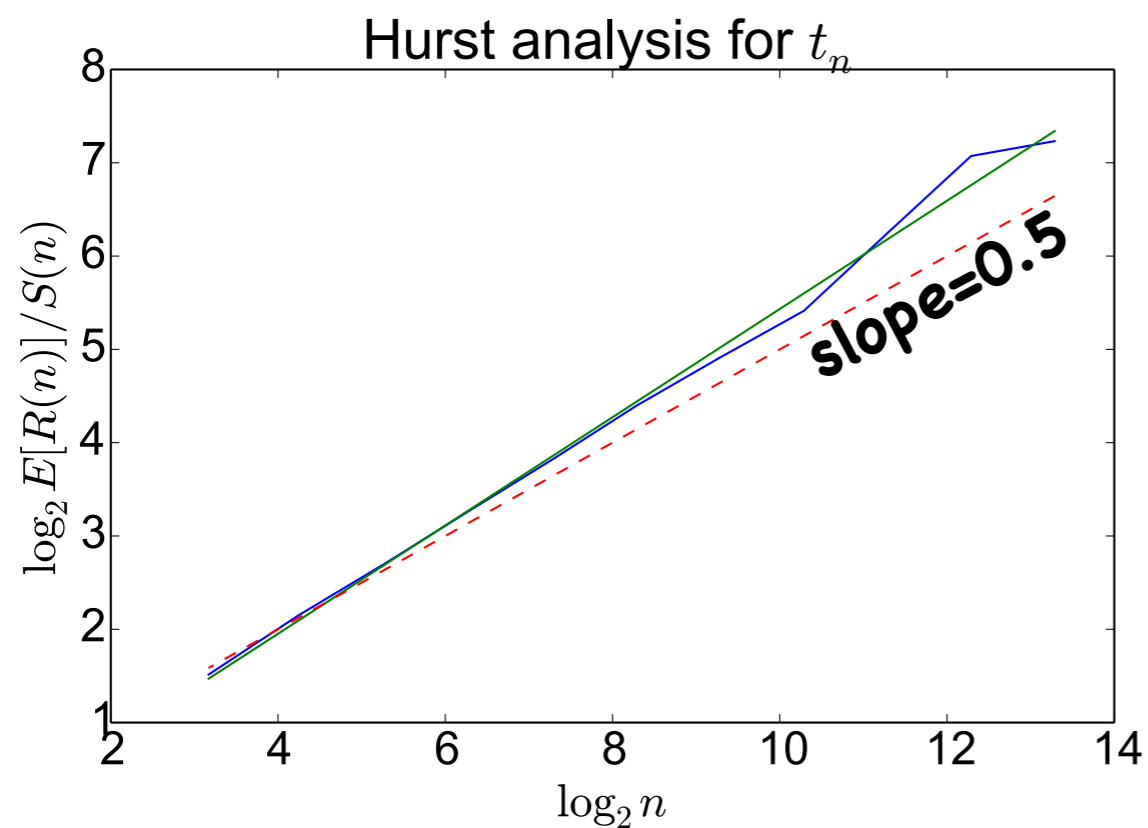
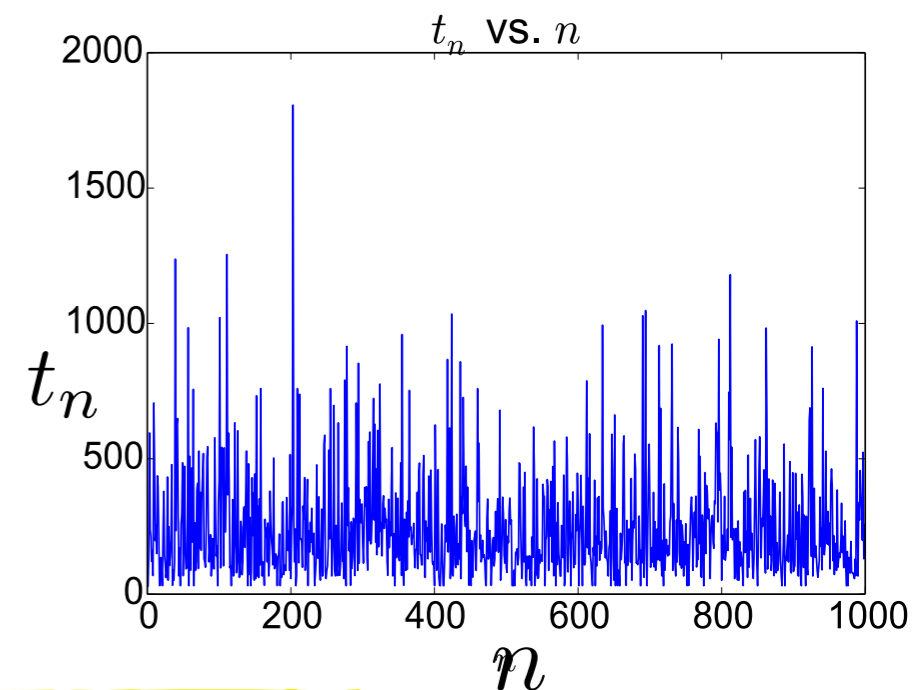
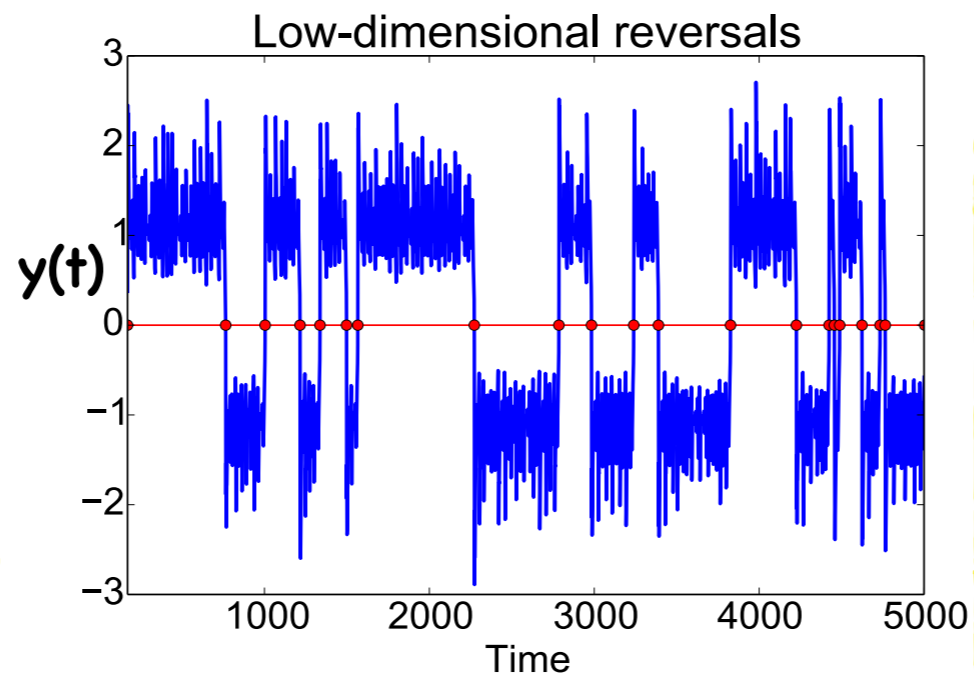
$E1$ and $E2$ curves. (a) u_z for $Ra = 659.0$ (b) u_z for Fourier mode (1,1) for $Ra = 659.0$

We can classify 'random' reversals in two classes:
(i) low-dimensional reversals, &
(ii) stochastic reversals.

Seeking Low Dimensionality

$$\begin{aligned}\dot{x} &= \mu x - zy, \\ \dot{y} &= -\nu x + zx, \\ \dot{z} &= \Gamma - z + xy.\end{aligned}$$

(Gissinger et al., 2010)



Conclusions

- There are two kinds of random reversals.
- Models should be constructed with Ra of convection in mind.
- Need to be careful with conclusions drawn from attractor reconstruction method.

...Thanks for your presence and patience!