On the Causality of Dynamical Systems

Thomas C. Fraser^{1,2}

¹Perimeter Institute for Theoretical Physics, Waterloo, Ontario, Canada, N2L 2Y5 ²Dept. of Physics and Astronomy, University of Waterloo, Waterloo, Ontario, Canada, N2L 3G1

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Disclaimers

1 A Chaotic Origin Story

1.1 Lorenz's Discovery

In "Deterministic nonperiodic flow" (Lorenz 1963), Lorenz (this is Edward Norton Lorenz, not to be confused with the physicist Ludvig Lorenz, or the actor Edward Norton) presented a simplified dynamical model for atmospheric convection, which today is known as the Lorenz system:

$$\frac{dX}{dt} = \sigma(Y - X),$$

$$\frac{dY}{dt} = X(\rho - Z) - Y,$$

$$\frac{dZ}{dt} = XY - \beta Z.$$
(1)

The Lorenz system was remarkable because despite its determinism and simplicity, it exhibits flows which are non-periodic, chaotic and yet bounded as in Figure 1. Moreover, Lorenz identifies the non-linearity of the equations as being essential for these features postulates their ubiquity.

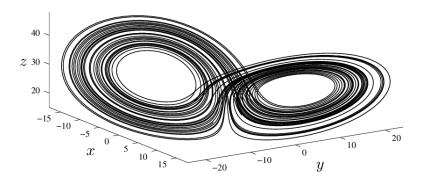


Figure 1: The strange attractor of the Lorenz system for $\sigma=10, \beta=8/3, \rho=28$ with X(0)=1.1, Y(0)=-1.9, Z(0)=13.1. Figure by P. T. Clemson.

Later in "On the nature of turbulence" (Ruelle and Takens 1971), Ruelle and Takens develop a variety of mathematics to study such quasi-periodic behaviors and refers to them as *strange attractors*. Importantly, they conjectured that universally, strange attractors where the cause of turbulent behaviors seen in fluid flow. This conjecture recieved further support after "Onset of turbulence in a rotating fluid" (Gollub and Swinney 1975).

1.2 What are attractors anyway?

What exactly is notion of an attractor? Intuitively, attractors generalize the more familiar notions of stability for differential equations such as stable fixed points and limit cycles in the sense that an attractor A is a compact subset such that points starting sufficiently close to A will remain in a given neighborhood of A. For a detailed account of the various notions and formulations of an attractor, see "On the concept of attractor" (Milnor 1985). Nevertheless, the following definition will be adequate.

A dynamical system on a manifold M (for example \mathbb{R}^n) is specified by a flow (a solution to the system of ODEs)

$$\Phi_{(\cdot)}(\cdot): \mathbb{R} \times M \to M, \tag{2}$$

where Φ_t is a diffeomorphism of M for all $t \in \mathbb{R}$ such that

$$\forall V \in M : \Phi_0(V) = V, \quad \text{and} \quad \forall s, t \in \mathbb{R} : \Phi_t \circ \Phi_s = \Phi_{s+t}. \tag{3}$$

An **attractor** is any $A \subseteq M$ which is

1. forward invariant

$$\forall a \in A, \forall t \geq 0 : \Phi_t(a) \in A,$$

2. admits an neighborhood B(A), called the **basin of attraction**, such for every open neighborhood N of A, there is a sufficiently large T such that

$$\forall b \in B(A), \forall t \geq T : \Phi_t(b) \in N,$$

3. and finally, there is no other proper subset $A' \subset A$ satisfying the above.

Note that some alternative defintions demand that A has non-zero measure (i.e. to eliminate stable fixed points) or that there exists a orbit of the flow that is dense inside A.

What makes a stange attractor so *strange*? At the time, Ruelle and Takens never articulated a concrete definition for strange attractors, instead is was simply an attractor that was "strange" to them. Today, strange attractors are defined to be attractors whose dimension is not an integer, i.e. a fractal. Of course, the Lorenz attractor is a strange attractor in this sense as well, as proven in "A rigorous ODE solver and Smale's 14th problem" (Tucker 2002).

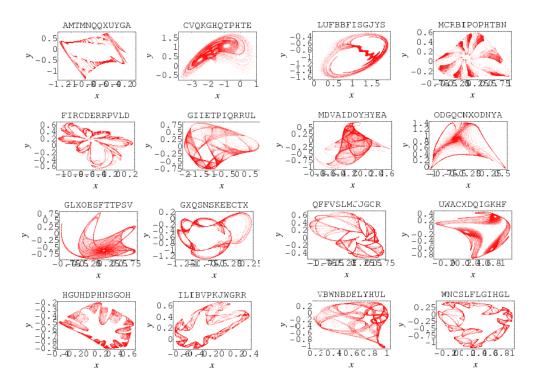


Figure 2: Some strange attractors. Figures from E. W. Weisstein.

1.3 Reconstructing Attractors

In "Geometry from a time series" (Packard et al. 1980), Packard et al. were interested in problem of dynamical reconstruction: from experimental observations of a turbulent fluid flow, how does one show the existence of a low-dimensional chaotic dynamical system which explains the observed behaviors? Additionally, how does one determine the dimensionality of the underlying attractor? They demonstrate their ideas using another non-linear dynamical system studied by (Rössler 1976):

$$\frac{\mathrm{d}X}{\mathrm{d}t} = -(Y+Z),$$

$$\frac{\mathrm{d}Y}{\mathrm{d}t} = X + 0.2Y,$$

$$\frac{\mathrm{d}Z}{\mathrm{d}t} = 0.4 + XZ - 5.7Z.$$
(4)

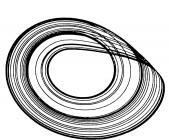


FIG. 1. (x,y) projection of Rossler (Ref. 7).

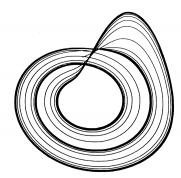


FIG. 2. (x,\dot{x}) reconstruction from the time series.

Figure 3: The Rössler system flow projected onto the X, Y plane and the induced flow of (X, \dot{X}, \ddot{X}) projected onto the X, \dot{X} plane. Figure from (Packard et al. 1980).

2 Attractors and Takens' Theorem

3 Selected References

3.1 Some Recent Developments in a Concept of Causality

Granger

3.2 Detecting Causality in Complex Ecosystems

Sugihara et al.

3.3 Distinguishing Time-delayed Causal Interactions using Convergent Cross Mapping

Ye et al.

3.4 Exact Inference of Causal Relations in Dynamical Systems

Benkő et al.

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