

Introduction to Scientific ML : Day 2

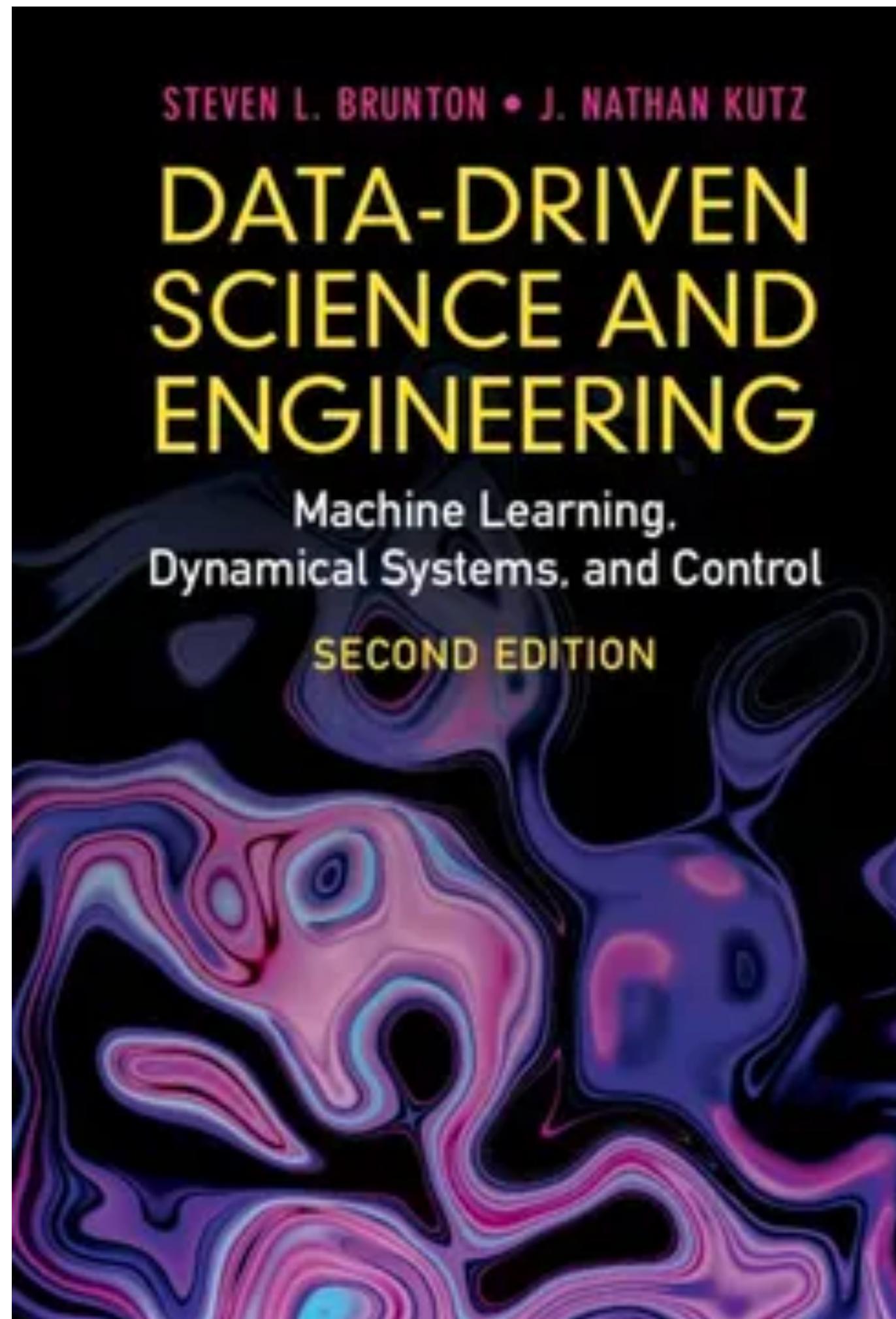
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UNIVERSITY *of*
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Data-driven science and engineering



Dimensionality Reduction and Transforms

- Singular value decomposition
- Fourier and Wavelet Transform
- Sparsity and Compressed Sensing
- ...

Machine learning and Data Analysis

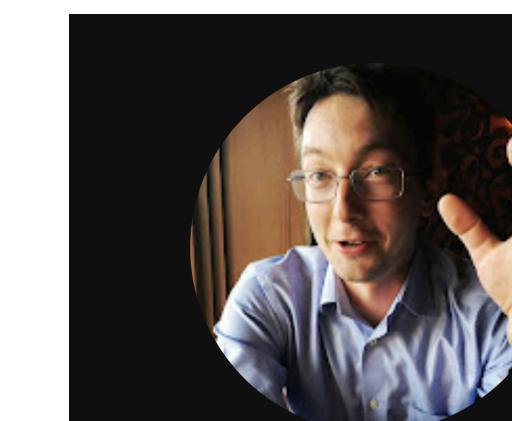
Dynamics and Control

- Data-driven Dynamical Systems
- Linear Control Theory
-

Advanced Data-Driven Modeling and Control

- Data-driven Control
- Reinforcement learning
- Physics informed Machine Learning

Videos for every section !!!



Steve Brunton

@Eigensteve 271K subscribers 464 videos

More about this channel >



What is a dynamical system?

We will agree to represent it as a **Nonlinear Ordinary Differential Equation**

$$\frac{d}{dt} \mathbf{x}(t) = \mathbf{f}(\mathbf{x}(t), t; \beta)$$

The vector $\mathbf{x} \in \mathbb{R}^n$ is the state of the system evolving in time t .

β are parameters.

\mathbf{f} is the vector field. Generally assumed to be Lipschitz continuous to guarantee existence and uniqueness.

Picard-Lindelöf theorem

Applications

Linear algebra
Numerical analysis
Topology
Geometry

Dynamical systems provide a **mathematical framework** to model interactions between **quantities** that **co-evolve in time**

Classical mechanics

Electrical circuits

Turbulent fluids

Climate science

Finance

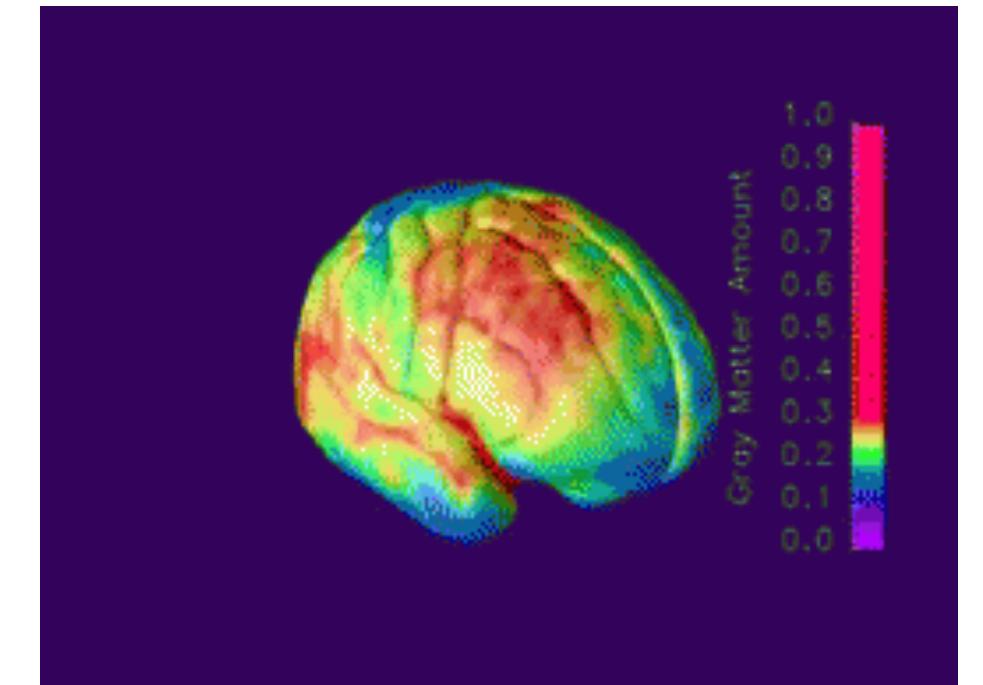
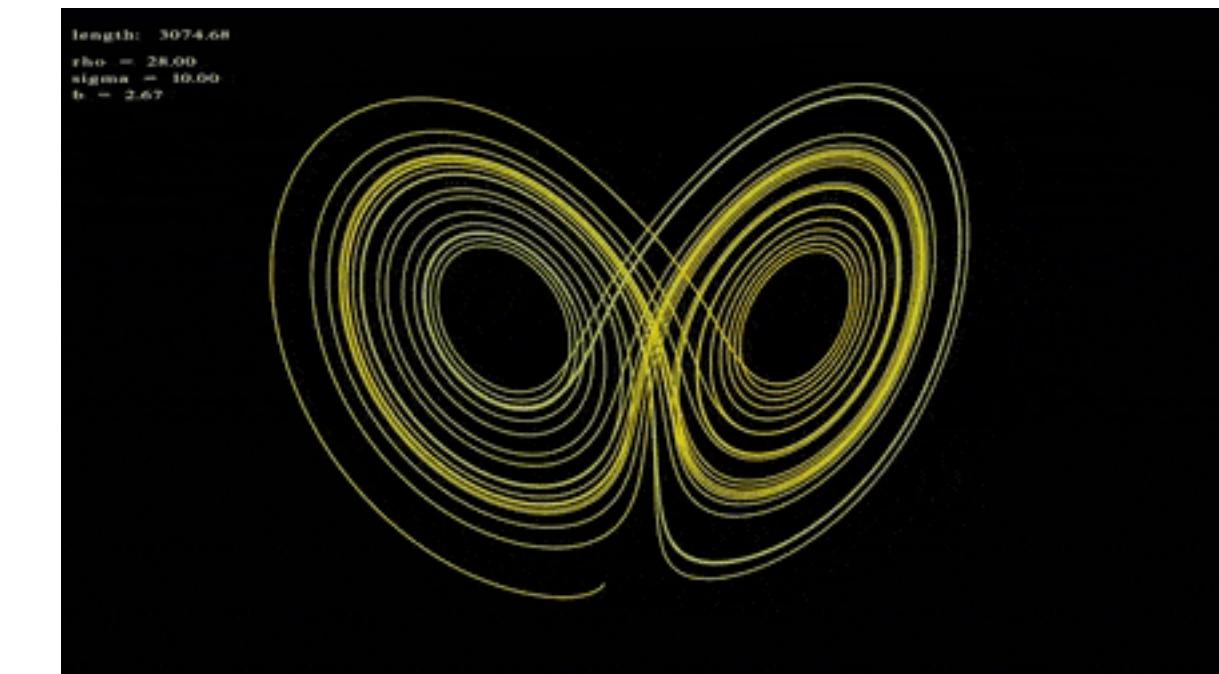
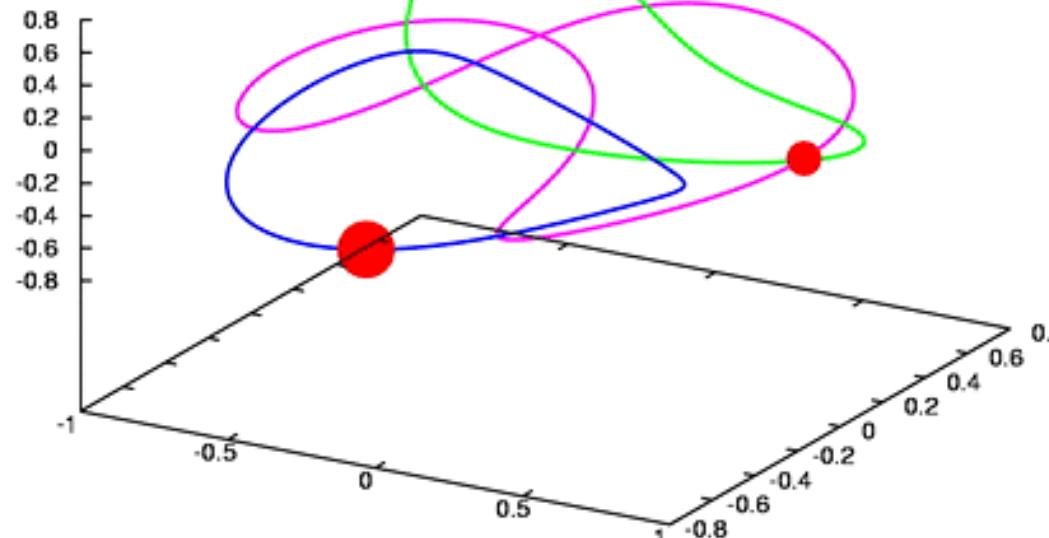
Ecology

Social systems

Neuroscience

Epidemiology

Seminal work by Poincaré on the 3-body problem



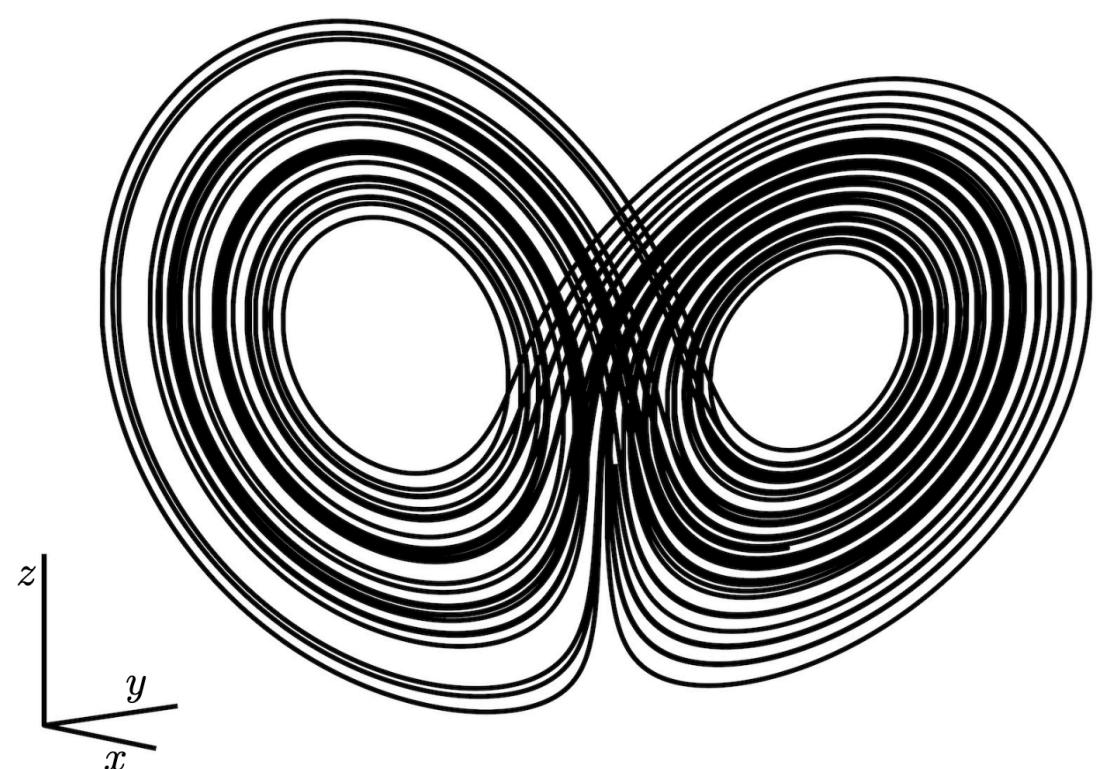
$$\frac{d}{dt}\mathbf{x}(t) = \mathbf{f}(\mathbf{x}(t), t; \boldsymbol{\beta})$$

Example: Lorenz equations

Consider the equations

$$\begin{aligned}\dot{x} &= \sigma(y - x) \\ \dot{y} &= x(\rho - z) - y \\ \dot{z} &= xy - \beta z\end{aligned}$$

With parameters $\sigma = 10$, $\rho = 28$, and $\beta = 8/3$. A trajectory of the Lorenz system



Simple system that exhibit chaos
(sensitive dependence of initial
conditions).

Goals and Challenges in Modern Dynamical Systems

Future state prediction

Long-time predictions

Design and optimization

Tune parameters of a system

Estimation and control

Control a DS through feedback

Interpretability and physical understanding

Provide insight through analyzing trajectories

More on CH. 7

Open source libraries

For data-driven dynamical systems

PyDMD

Dynamic Mode Decomposition for a data-driven model simplification based on spatiotemporal coherent structures

PySINDy

TODAY

PyKoopman

Data-driven approximations to the Koopman operator.

Sparse regression package with several implementations for the Sparse Identification of Nonlinear Dynamical systems

Data-driven dynamical systems toolbox

Implementation of the algorithms used in several papers. Includes optimizations in C++

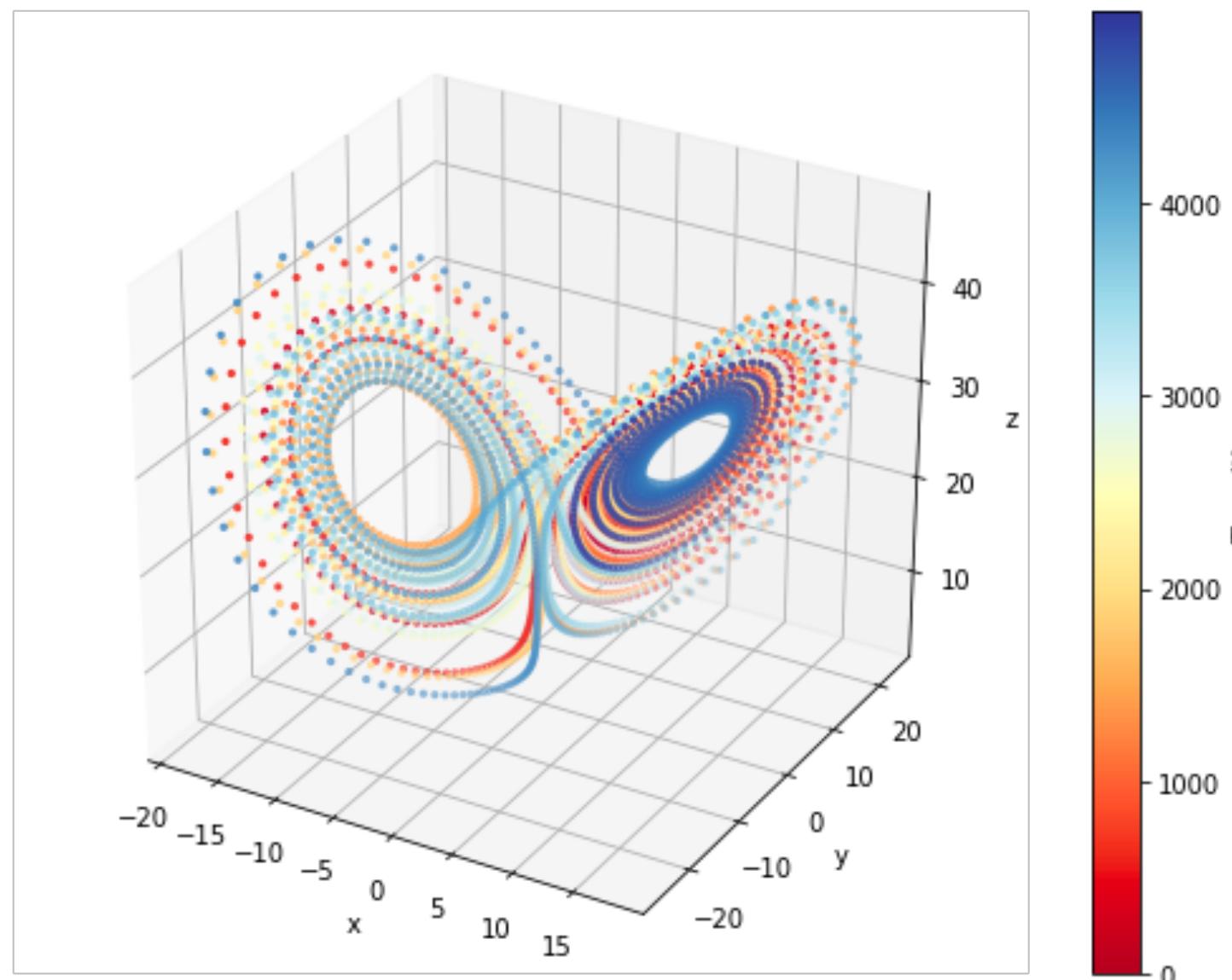
Deeptime

Estimate dynamical models based on time-series data including conventional linear learning methods, such as Markov State Models (MSMs), Hidden Markov Models (HMMs) and Koopman models, as well as kernel and deep learning approaches such as VAMPnets and deep MSMs

Sparse identification of Nonlinear Dynamical Systems

Brunton, Proctor, Kutz (2016) PNAS

Data



SINDy

Dynamics (ODE)

$$\dot{x} = \sigma(y - x)$$

$$\dot{y} = x(\rho - z) - y$$

$$\dot{z} = xy - \beta z$$

Goal: We wish to identify the governing equations that generated the observed data.

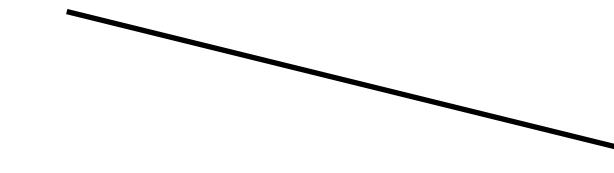


Nathan Kutz, Steve Brunton and Joshua Proctor (from left to right).

Main ideas

Suppose we have a set of measurements $\mathbf{x}(t) \in \mathbb{R}^n$ from some physical system at different points in time t .

SINDy seeks to represent the time evolution of $\mathbf{x}(t)$ in terms of a nonlinear function \mathbf{f} :

$$\frac{d}{dt} \mathbf{x}(t) = \mathbf{f}(\mathbf{x}(t)) .$$


How the system evolves in time.

This equation constitutes a dynamical system for the measurements $\mathbf{x}(t)$.

The vector $\mathbf{x}(t) = [x_1(t), x_2(t), \dots x_n(t)]^\top$ gives the state of the physical system at time t .

Main ideas

The key idea behind SINDy is that the function f is often **sparse** in the space of an appropriate set of basis functions.

For example, the function

$$\frac{d}{dt}\mathbf{x} = \mathbf{x}(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) \\ f_2(\mathbf{x}) \end{bmatrix} = \begin{bmatrix} 1 - x_1 + 3x_1x_2 \\ x_2^2 - 5x_1^3 \end{bmatrix}$$

is sparse with respect to the set of polynomials of two variables in the sense that if we were to write an expansion of the component functions of f in this basis, e.g.

$$f_1(x) = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} a_{i,j} x_1^i x_2^j$$

only a small number of coefficients $a_{i,j}$ would be nonzero.

SINDy employs **sparse regression** to find a linear combination of basis functions that best capture the dynamic behavior of the physical system.

Main ideas

The **key idea** behind SINDy is that the function f is often **sparse** in the space of an appropriate set of basis functions.

SINDy seeks to approximate f by a generalized linear model

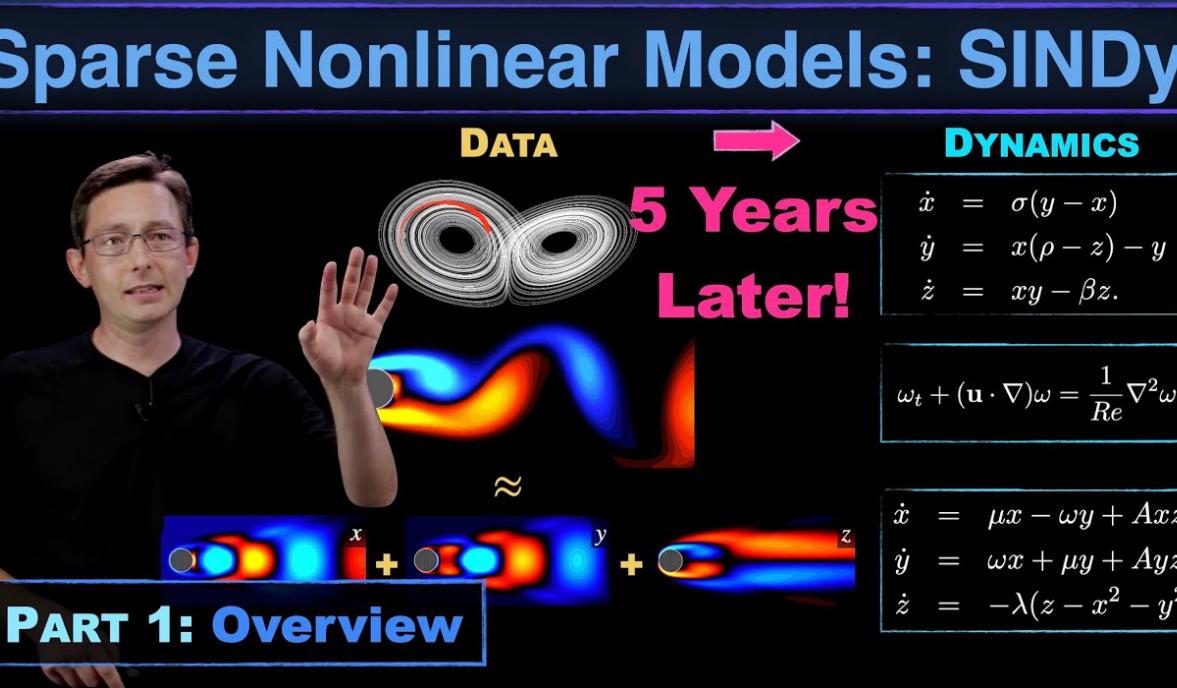
$$f(\mathbf{x}) \approx \sum_{k=1}^p \theta_k(\mathbf{x}) \xi_k = \Theta(\mathbf{x}) \xi$$

With the fewest non-zero terms in ξ as possible.

Could you name a sparse regression algorithm ?

What type of penalization on the vector of parameters do we choose ?

SINDy employs **sparse regression** to find a linear combination of basis functions that best capture the dynamic behavior of the physical system.



Method

1. **Input measurements.** Time-series data is collected

$$\mathbf{X} = \left(\mathbf{x}(t_1) \quad \mathbf{x}(t_2) \quad \dots \quad \mathbf{x}(t_m) \right)^T$$

2. **Differentiation.** Construct a similar matrix of derivatives

$$\dot{\mathbf{X}} = \left(\dot{\mathbf{x}}(t_1) \quad \dot{\mathbf{x}}(t_2) \quad \dots \quad \dot{\mathbf{x}}(t_m) \right)^T$$

3. **Feature library.** Construct a library of candidate nonlinear functions from \mathbf{X}

$$\Theta(\mathbf{X}) = (1 \quad \mathbf{X} \quad \mathbf{X}^2 \quad \dots \quad \mathbf{X}^d \quad \dots \quad \sin(\mathbf{X}) \quad \dots)$$

All possible d-th degree polynomials

Domain specific knowledge

Be careful with noisy data

Method

A **parsimonious model** will provide an accurate model fit in

$$\dot{\mathbf{X}} = \Theta(\mathbf{X})\boldsymbol{\Xi}$$

with as few terms as possible in $\boldsymbol{\Xi}$.

Identify the model via convex ℓ_1 -regularized sparse regression:

$$\boldsymbol{\xi}_k = \operatorname{argmin}_{\boldsymbol{\xi}'_k} \left\| \dot{\mathbf{X}}_k - \Theta(\mathbf{X})\boldsymbol{\xi}'_k \right\|_2 + \lambda \left\| \boldsymbol{\xi}'_k \right\|_1$$

- LASSO
- Sequential thresholded least-squares

k -th column of $\dot{\mathbf{X}}$

sparsity-promoting knob

Method

A **parsimonious model** will provide an accurate model fit in

$$\dot{\mathbf{X}} = \Theta(\mathbf{X})\boldsymbol{\Xi}$$

with as few terms as possible in $\boldsymbol{\Xi}$.

The sparse vectors ξ_k may be synthesized into a dynamical system

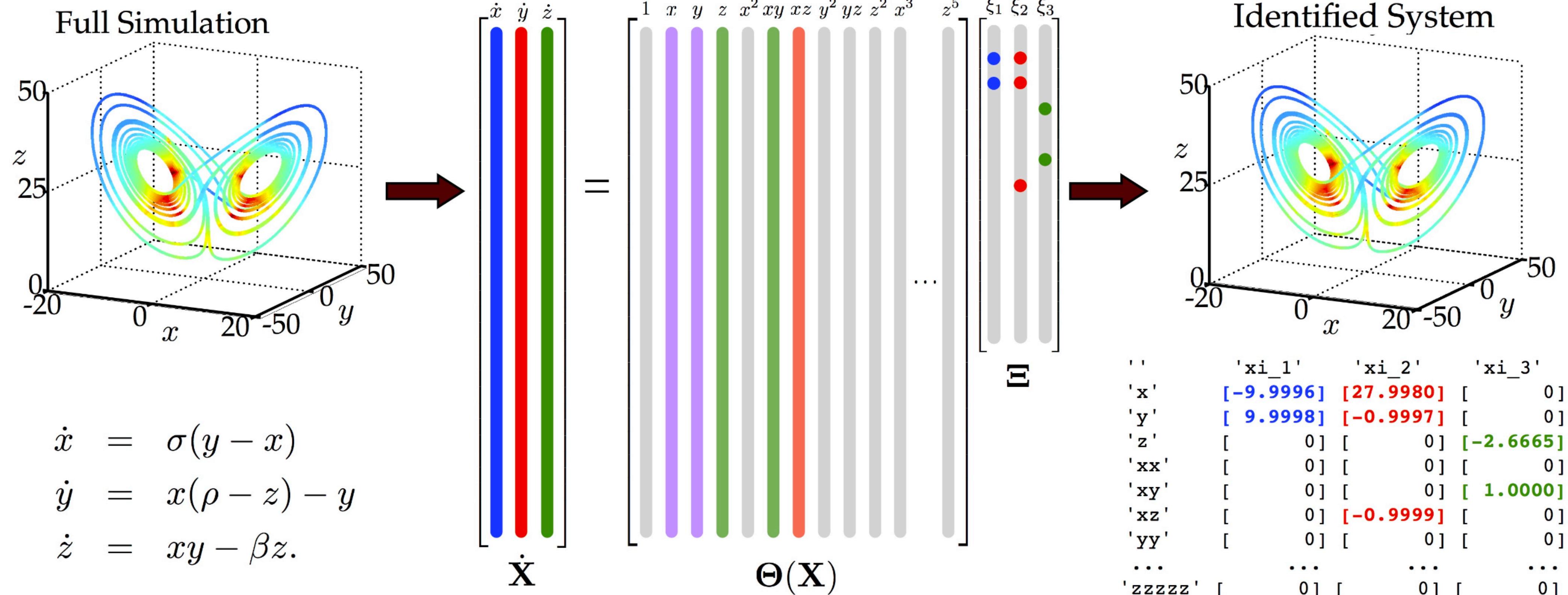
$$\dot{x}_k = \Theta(\mathbf{x})\xi_k$$

k -th element of $\dot{\mathbf{x}}$

row vector of symbolic functions of $\dot{\mathbf{x}}$

Schematic overall view

Parsimonious model is selected



Let's run the demo