

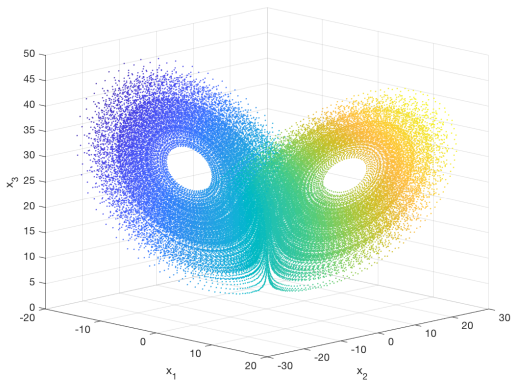
Reproducing Kernel Hilbert Space Approaches for Spectral Analysis of Dynamical Systems

Dimitris Giannakis
Center for Atmosphere Ocean Science
Courant Institute of Mathematical Sciences
New York University

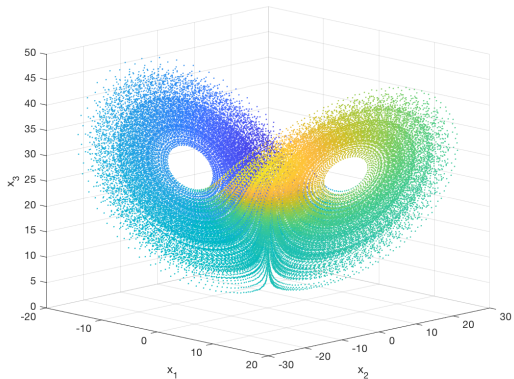
Operator Theoretic Methods in Dynamic Data Analysis and Control
IPAM, February 15, 2019

Collaborators: Shuddho Das, Joanna Slawinska

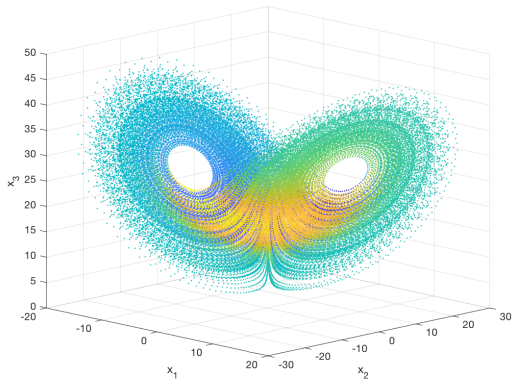




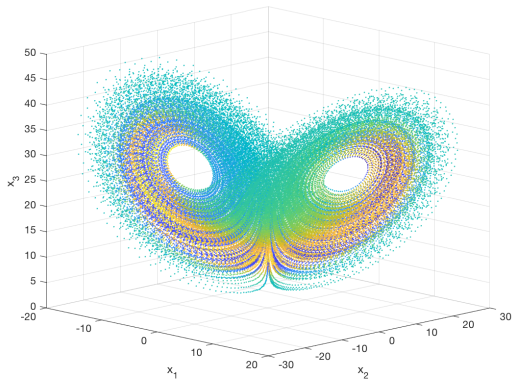
$$f(x) = x_1, \quad x = (x_1, x_2, x_3)$$



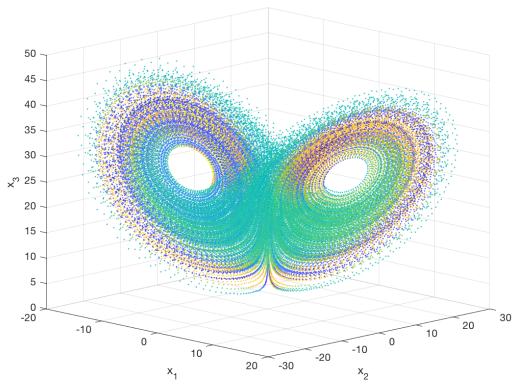
$$f(\Phi^t(x)), \quad t = 0.2$$



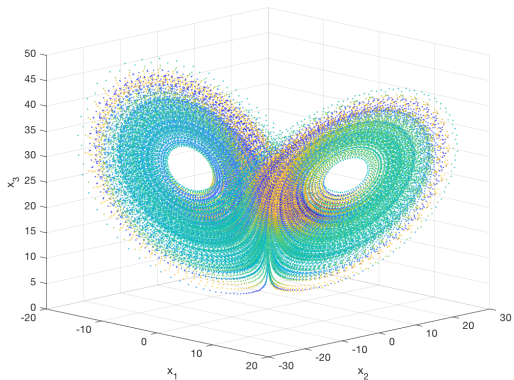
$$f(\Phi^t(x)), \quad t = 0.4$$



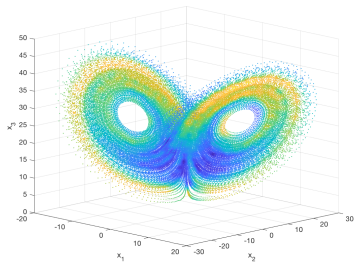
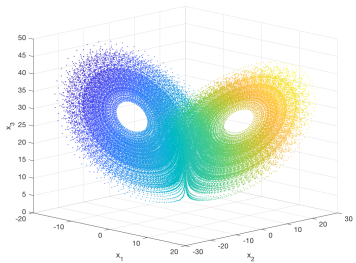
$$f(\Phi^t(x)), \quad t = 0.6$$



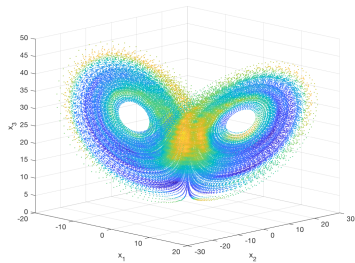
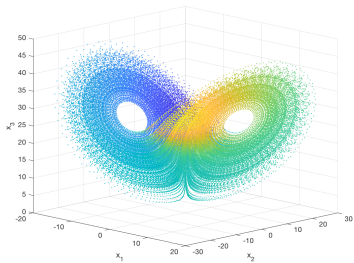
$$f(\Phi^t(x)), \quad t = 0.8$$



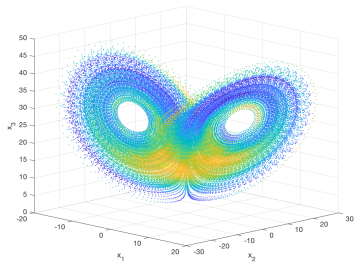
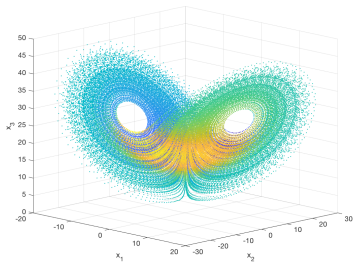
$$f(\Phi^t(x)), \quad t = 1$$



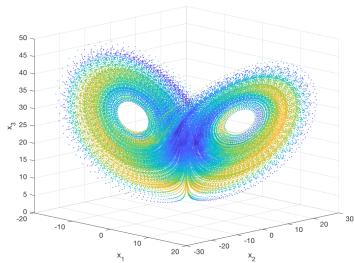
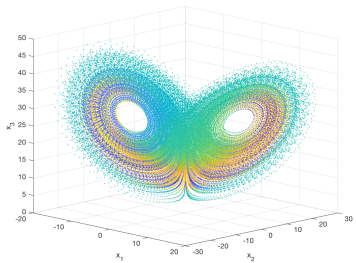
$t = 0$



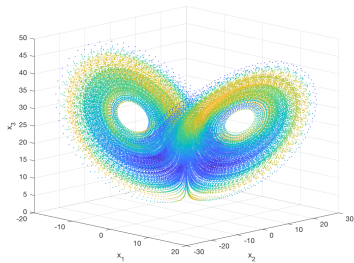
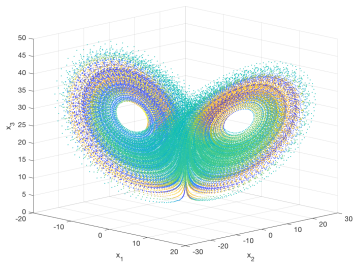
$t = 0.2$



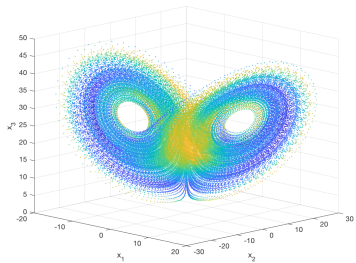
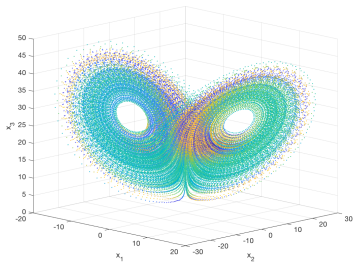
$t = 0.4$



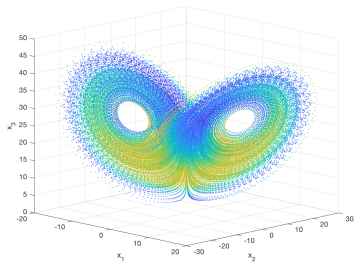
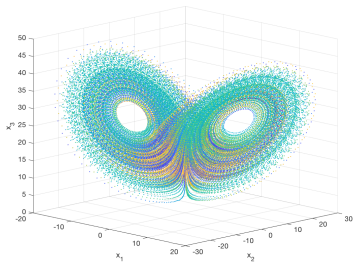
$t = 0.6$



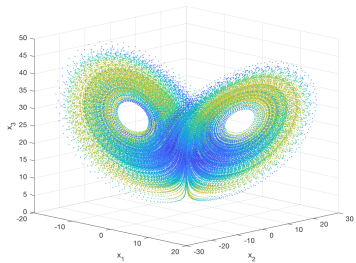
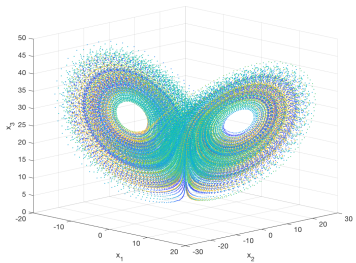
$t = 0.8$



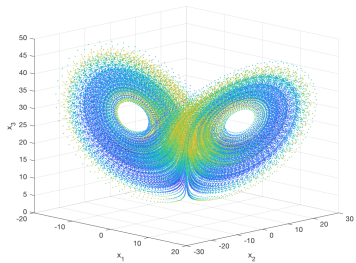
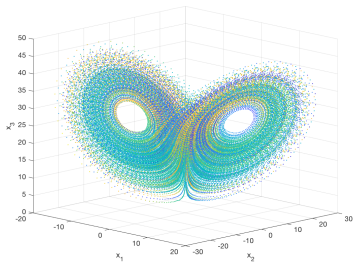
$t = 1$



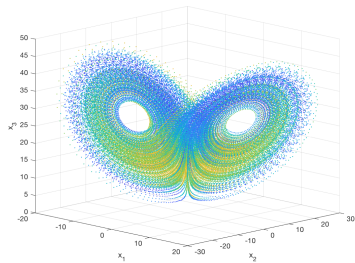
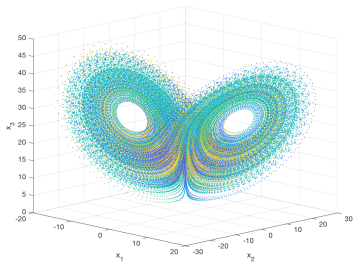
$t = 2$



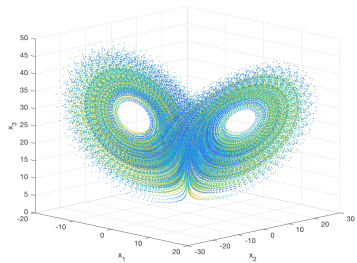
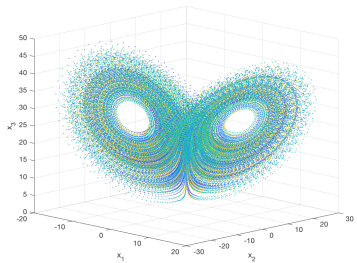
$t = 3$



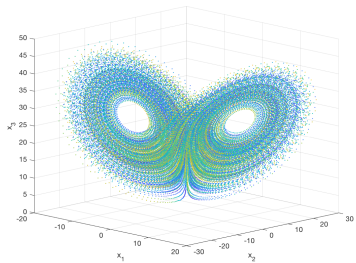
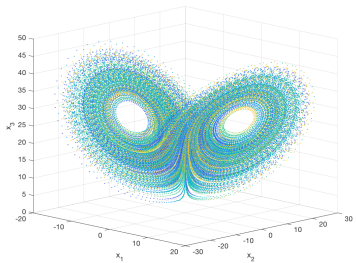
$t = 4$



$t = 5$

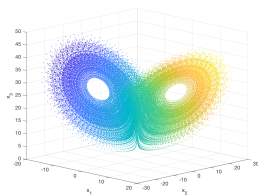


$t = 15$



$t = 20$

Setup and basic assumptions



- Continuous flow $\Phi^t : \mathcal{M} \rightarrow \mathcal{M}$, $t \in \mathbb{R}$, on metric space \mathcal{M}
- Ergodic, invariant Borel probability measure μ with compact support $X \subseteq \mathcal{M}$
- Forward-invariant, compact, C^1 manifold $M \subseteq \mathcal{M}$, s.t. $X \subseteq M$ and $\Phi^t|_M$ is C^1
- Koopman operators $U^t : f \mapsto f \circ \Phi^t$ on $C^0(M)$, $L^2(\mu)$
- Generator $V : D(V) \rightarrow L^2(\mu)$,

$$D(V) \subset L^2(\mu), \quad V^* = -V, \quad Vf = \lim_{t \rightarrow 0} (U^t f - f)/t$$

- Projection-valued measure $E : \mathcal{B}(\mathbb{R}) \rightarrow \mathcal{L}(L^2(\mu))$,

$$V = \int_{\mathbb{R}} i\omega dE(\omega), \quad U^t = \int_{\mathbb{R}} e^{i\omega t} dE(\omega)$$

Objectives

- 1 Identify **coherent observables** under the dynamics
(*spectral approximation of operators*)
 - 2 Perform **forecasting** of observables
(*pointwise approximation of operators*)
- Challenges due to infinite dimensionality include the presence of **unbounded operators** and **continuous spectra**
 - Methods should be **data-driven**, i.e., only utilize information from a time-ordered sequence of measurements
 - Many operator theoretic techniques developed to address these objectives
(Dellnitz & Junge 1999; Dellnitz & Froyland 2000; Mezić & Banaszuk 2004; Mezić 2005; Rowley et al. 2009; Schmidt 2010; Froyland et al. 2014; Berry et al. 2015; Froyland 2015; Williams et al. 2015; Klus et al. 2016; Brunton et al. 2017; G. 2017; Das & G. 2017; Wu & Noé 2017; Korda et al. 2018; ...)
 - Here, discuss approaches to address these objectives using ideas from **reproducing kernel Hilbert space (RKHS) theory** (Das et al. 2018)

	$C^0(M)$	$L^2(\mu)$	RKHS \mathcal{H}
Pointwise evaluation	✓	✗	✓
Inner product	✗	✓	✓
Dynamics-intrinsic	✓	✓	✗

Reproducing kernel Hilbert spaces

An RKHS \mathcal{H} on M is a Hilbert space of functions $f : M \rightarrow \mathbb{C}$ such that, for every $x \in M$, the **evaluation functional** $J_x : f \mapsto f(x)$ is bounded

Every RKHS \mathcal{H} has a unique **reproducing kernel**, $k : M \times M \rightarrow \mathbb{C}$ s.t.

- 1 $k(x, \cdot) \in \mathcal{H}$, $\forall x \in M$
- 2 $k(x, y) = k(y, x)^*$, $\forall x, y \in M$
- 3 For every $x_0, \dots, x_{n-1} \in M$, the $n \times n$ kernel matrix $\mathbf{K} = [k(x_i, x_j)]$ is positive-semidefinite
- 4 For every $x \in M$ and $f \in \mathcal{H}$, $f(x) = J_x f = \langle k(x, \cdot), f \rangle_{\mathcal{H}}$

Conversely, for every $k : M \times M \rightarrow \mathbb{C}$ satisfying the above properties, there exists a unique RKHS \mathcal{H} with k as its reproducing kernel (Moore-Aronszajn thm.)

If $k \in C^r(M \times M)$, then $\mathcal{H} \subset C^r(M)$, and the inclusion $\mathcal{H} \hookrightarrow C^r$ is bounded (Ferreira & Menegatto 2013)

RKHS and integral operators

Let ν be a finite Borel measure on M with compact support $X_\nu \subseteq M$, and \mathcal{H} an RKHS with continuous reproducing kernel k

- The following **integral operator** $K : L^2(\nu) \rightarrow \mathcal{H}$ is well-defined:

$$K : f \mapsto \int_M k(\cdot, x) f(x) d\nu(x)$$

- K^* coincides with the inclusion map $C^0(M) \hookrightarrow L^2(\nu)$
- $G = K^*K$ is a self-adjoint, positive-semidefinite, trace-class integral operator on $L^2(\nu)$
- There exists an orthonormal basis $\{\phi_0, \phi_1, \dots\}$ of $L^2(\nu)$ consisting of eigenfunctions of G at real eigenvalues $\lambda_0 \geq \lambda_1 \geq \dots \searrow 0$
- $\psi_j = K\phi_j/\lambda_j^{1/2}$, $\lambda_j > 0$, forms an orthonormal basis of $\overline{\text{ran } K} \subseteq \mathcal{H}$
- $k(x, y) = \sum_j \psi_j(x)\psi_j(y)$, uniformly for $x, y \in X_\nu$ (Mercer thm.)
- k is said to be **$L^2(\nu)$ -strictly-positive** if $G > 0$
- k is said to be **$L^2(\nu)$ -Markov ergodic** if (i) $Gf = f$ iff. $f = \text{const}$; (ii) $Gf \geq 0$ if $f \geq 0$; (iii) $\langle 1, Gf \rangle_\mu = \langle 1, f \rangle_\mu$

Nyström extension

Let $H = \text{ran } K^* \subseteq L^2(\nu)$, and define $\mathcal{N} : H \rightarrow \mathcal{H}$ s.t.

$$\mathcal{N} : \sum_j c_j \phi_j \mapsto \sum_j \lambda_j^{-1/2} c_j \psi_j$$

- $\mathcal{N}f$ is an **extension** of f in the sense that $K^* \mathcal{N}f = f$
- $\text{ran } \mathcal{N} = \overline{\text{ran } K}$, and $\mathcal{N}^\dagger = K^*$
- H acquires Hilbert space structure via the inner product $\langle f, g \rangle_H = \langle \mathcal{N}f, \mathcal{N}g \rangle_{\mathcal{H}}$; $H \hookrightarrow L^2(\nu)$ then becomes a compact embedding
- If k is $L^2(\nu)$ -strictly-positive, H is a dense subspace of $L^2(\nu)$
- If k is $L^2(\nu)$ -Markov ergodic, $\|f\|_H \geq \|f\|_{L^2(\nu)}$, with equality iff $f = \text{const.}$
- The associated **Dirichlet energy** $\mathcal{D} : H \rightarrow \mathbb{R}_+$ then assigns a measure of **roughness** of functions in H ,

$$\mathcal{D}(f) = \frac{\|f\|_H^2}{\|f\|_{L^2(\nu)}^2} - 1$$

Eigenfunctions of G_N on the L63 attractor

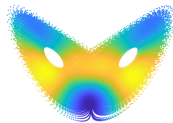
$\phi_1, \lambda_1 = 0.999$



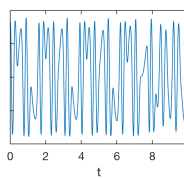
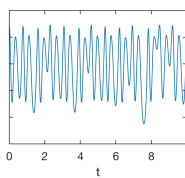
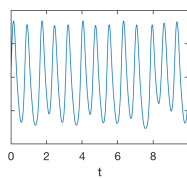
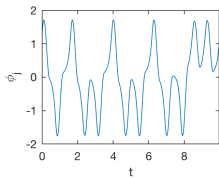
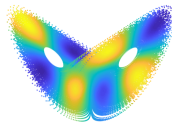
$\phi_2, \lambda_2 = 0.997$



$\phi_6, \lambda_6 = 0.972$



$\phi_8, \lambda_8 = 0.95$



RKHS compactification schemes for the generator

Because V is a skew-adjoint extension of the dynamical vector field $\vec{V} : C^1(M) \rightarrow L^2(\mu)$, given an RKHS \mathcal{H} with C^1 reproducing kernel k ,

$$\text{ran } G = \text{ran } K^* K \subseteq \text{ran } K^* \subset D(V)$$

Pre-smoothing:

- $A = VG$ is a Hilbert-Schmidt integral operator on $L^2(\mu)$ with C^0 kernel $k'(\cdot, x) = \vec{V}k(\cdot, x)$, i.e.,

$$Af = \int_M k'(\cdot, x) f(x) d\mu(x)$$

Post-smoothing:

- $\overline{GV} : D(V) \rightarrow L^2(\mu)$ is a densely-defined bounded operator, whose closure, $\overline{GV} = (GV)^{**} =: B$ is equal to $-A^*$, i.e.,

$$GV \subset -A^* = B, \quad Bf = - \int_M k'(x, \cdot) f(x) d\mu(x)$$

RKHS compactification schemes for the generator

Skew-adjoint compactification on \mathcal{H} :

- $W = KVK^*$ is a skew-adjoint, Hilbert-Schmidt operator on \mathcal{H} given by

$$Wf = - \int_M k'(x, \cdot) f(x) d\mu(x)$$

- The operator $K^*WN : H \rightarrow L^2(\mu)$ is a restriction of B

Skew-adjoint compactification on $L^2(\mu)$:

- $G^{1/2}VG^{1/2}$ is a densely-defined, bounded, antisymmetric operator, whose closure is a skew-adjoint, Hilbert-Schmidt operator $\tilde{V} : L^2(\mu) \rightarrow L^2(\mu)$
- There is a partial isometry $\mathcal{U} : L^2(\mu) \rightarrow \mathcal{H}$, given by the polar decomposition $K = \mathcal{U}G^{1/2}$, s.t. $\tilde{V} = \mathcal{U}^*W\mathcal{U}$

Spectra of the compactified generators

Let k be $L^2(\mu)$ -strictly-positive, Markov ergodic, and define $\mathcal{K} = \overline{\text{ran } K} \subseteq \mathcal{H}$

- A, B, \tilde{V} , and $W|_{\mathcal{K}}$ have the same, purely imaginary, spectra, including multiplicities of eigenvalues
- There exist orthonormal bases $\{\tilde{z}_0, \tilde{z}_1, \dots\}$ and $\{\zeta_0, \zeta_1, \dots\}$ of $L^2(\mu)$ and \mathcal{K} , respectively, s.t.,

$$\tilde{V}\tilde{z}_j = i\omega_j z_j, \quad W\zeta_j = i\omega_j \zeta_j, \quad \omega_j \in \mathbb{R}, \quad \zeta_j = \mathcal{U}z_j$$

- 0 is a simple eigenvalue of A, B, \tilde{V} , and $W|_{\mathcal{K}}$ corresponding to constant eigenfunctions
- $z'_j = G^{-1/2}\tilde{z}_j$ and $z_j = G^{1/2}\tilde{z}_j$ are eigenfunctions of A and B , respectively, and $\{z'_0, z'_1, \dots\}$ and $\{z_0, z_1, \dots\}$ form biorthogonal, unconditional Schauder bases of $L^2(\mu)$
- The following expansions converge in operator norm:

$$W = \sum_{j=0}^{\infty} i\omega_j \langle \zeta_j, \cdot \rangle_{\mathcal{H}} \zeta_j, \quad \tilde{V} = \sum_{j=0}^{\infty} i\omega_j \langle \tilde{z}_j, \cdot \rangle_{L^2(\mu)} \tilde{z}_j$$

- The following expansions converge strongly:

$$A = \sum_{j=0}^{\infty} i\omega_j \langle z_j, \cdot \rangle_{L^2(\mu)} z'_j, \quad B = \sum_{j=0}^{\infty} i\omega_j \langle z'_j, \cdot \rangle_{L^2(\mu)} z_j$$

Functional calculus

- Associated with \tilde{V} and W are unique, purely-atomic **projection-valued measures (PVMs)** $E : \mathcal{B}(\mathbb{R}) \rightarrow \mathcal{L}(L^2(\mu))$ and $\mathcal{E} : \mathcal{B}(\mathbb{R}) \rightarrow \mathcal{L}(\mathcal{H})$, s.t.

$$\tilde{E}(\Omega) = \sum_{j:\omega_j \in \Omega} \langle \tilde{z}_j, \cdot \rangle_{L^2(\mu)} \tilde{z}_j, \quad \mathcal{E}(\Omega) = \sum_{j:\omega_j \in \Omega} \langle \zeta_j, \cdot \rangle_{\mathcal{H}} \zeta_j + 1_{\Omega}(0) \text{proj}_{\mathcal{K}^\perp}$$

$$\tilde{E}(\Omega) = \mathcal{U}^* \mathcal{E}(\Omega) \mathcal{U}$$

$$\tilde{V} = \int_{\mathbb{R}} i\omega \, d\tilde{E}(\omega), \quad W = \int_{\mathbb{R}} i\omega \, d\mathcal{E}(\omega)$$

- Given a Borel-measurable function $Z : i\mathbb{R} \rightarrow \mathbb{C}$, we compute

$$Z(\tilde{V}) = \int_{\mathbb{R}} Z(i\omega) \, d\tilde{E}(\omega) = \sum_{j=0}^{\infty} Z(i\omega_j) \langle \tilde{z}_j, \cdot \rangle_{L^2(\mu)} \tilde{z}_j,$$

$$Z(W) = \int_{\mathbb{R}} Z(i\omega) \, d\mathcal{E}(\omega) = \sum_{j=0}^{\infty} Z(i\omega_j) \langle \zeta_j, \cdot \rangle_{\mathcal{H}} \zeta_j + Z(0) \text{proj}_{\mathcal{K}^\perp}$$

- Being non-normal, A and B generally do not have associated PVMs, but it is still possible to define an associated **holomorphic functional calculus**

Spectral convergence

Let $\{k_\tau\}_{\tau>0}$ be a one-parameter family of C^1 , $L^2(\mu)$ -strictly-positive kernels s.t., as $\tau \rightarrow 0^+$,

- 1 $G_\tau = K_\tau^* K_\tau \rightarrow I$, pointwise on $L^2(\mu)$
- 2 $\tilde{V}_\tau \rightarrow V$, pointwise on $D(V^2) \subset D(V)$

$D(V^2)$ is a **core** for V , and as a result condition 2 implies that \tilde{V}_τ converges to V in **strong resolvent sense**

The latter, in conjunction with compactness and skew-adjointness of the approximating operators \tilde{V}_τ implies in turn the following:

- As $\tau \rightarrow 0^+$, B_τ converges strongly to V on $D(V)$
- For every bounded, continuous function $Z : i\mathbb{R} \rightarrow \mathbb{C}$, as $\tau \rightarrow 0^+$, $Z(\tilde{V}_\tau)$ and $K_\tau^* Z(W_\tau) \mathcal{N}_\tau$ converge strongly to $Z(V)$
- For every bounded Borel-measurable set $\Omega \subset \mathbb{R}$ such that $E(\partial\Omega) = 0$, as $\tau \rightarrow 0^+$, $\tilde{E}_\tau(\Omega)$ and $K_\tau^* \mathcal{E}_\tau(\Omega) \mathcal{N}_\tau$ converge strongly to $E(\Omega)$
- For every element of the spectrum $i\omega$ of V , there exists a sequence of eigenvalues $i\omega_\tau$ of \tilde{V}_τ (and A_τ , B_τ , W_τ) converging to $i\omega$ as $\tau \rightarrow 0^+$

Markov semigroups

To construct a one-parameter family of kernels meeting the previously stated conditions:

- 1 Start from a C^1 , $L^2(\mu)$ -strictly positive, Markov ergodic kernel $p : M \times M \rightarrow \mathbb{R}$, constructed, e.g., by normalization of an unnormalized kernel (Coifman & Hirn 2013)
- 2 Compute the eigenvalues and eigenfunctions of the associated operator $G = P^*P : L^2(\mu) \rightarrow L^2(\mu)$, i.e., $G\phi_j = \lambda_j\phi_j$, and $1 = \lambda_0 > \lambda_1 \geq \lambda_2 \geq \dots > 0$
- 3 For every $\tau > 0$ and $x, y \in M$, define

$$p_\tau(x, y) = \sum_{j=0}^{\infty} \frac{e^{-\tau\eta_j}}{\lambda_j} \psi_j(x)\psi_j(y), \quad \eta_j = \frac{1}{\lambda_j} - 1, \quad \psi_j = \frac{1}{\lambda_j^{1/2}} P\phi_j$$

Then, the following hold:

- The series for $p_\tau(x, y)$ converges to a C^1 reproducing kernel p_τ of an RKHS $\mathcal{H}_\tau \subset \mathcal{H}$ in $C^1(M \times M)$ norm
- \mathcal{H}_τ has an orthonormal basis with elements $\psi_{\tau,j} = e^{-\tau\eta_j/2} P\phi_j$, and $\mathcal{H}_{\tau_1} \subseteq \mathcal{H}_{\tau_2}$ whenever $\tau_1 \geq \tau_2$
- Defining $G_0 = I$ and $G_\tau = P_\tau^* P_\tau$, the family $\{G_\tau\}_{\tau \geq 0}$ is a strongly continuous, self-adjoint, Markov semigroup
- As $\tau \rightarrow 0^+$, the corresponding approximate generator \tilde{V}_τ is **of trace class**, and converges to V , pointwise on $D(V)$, as required

Coherent pattern extraction

- Given $t \in \mathbb{R}$ and $\epsilon > 0$, a complex number γ is said to lie in the **ϵ -approximate point spectrum of U^t** if there exists a nonzero $f \in L^2(\mu)$ such that

$$\|U^t f - \gamma f\|_{L^2(\mu)} < \epsilon \|f\|_{L^2(\mu)}$$

- Define $R : \mathbb{R}_+ \times \mathbb{R}_+ \rightarrow \mathbb{R}$,

$$R(\epsilon, \tau) := \sup\{T > 0 : \|(U^t - e^{tB_\tau})P^*\| < \epsilon, \forall t \in [-T, T]\}$$

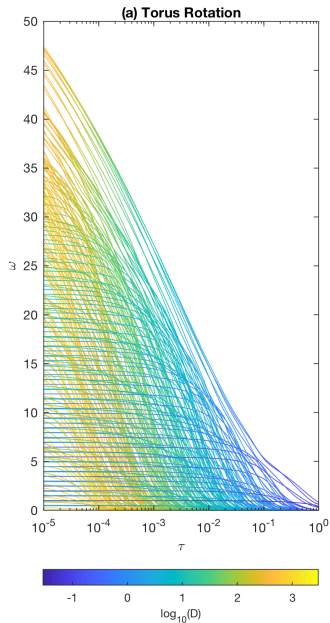
Let $(i\omega_\tau, \zeta_\tau)$ be an eigenpair of W_τ . Then, $(e^{i\omega_\tau t}, \tilde{z}_\tau)$, with $\tilde{z}_\tau = P_\tau^* \zeta_\tau$, is an ϵ -approximate eigenpair of U^t for all $t \in (-\mathcal{T}(\epsilon, \tau), \mathcal{T}(\epsilon, \tau))$, where

$$\mathcal{T}(\epsilon, \tau) = R(\epsilon, \tau) / \sqrt{\mathcal{D}(\tilde{z}_\tau) + 1}.$$

In addition:

- If $\lim_{\tau \rightarrow 0^+} \omega_\tau =: \omega$ exists, and $\mathcal{T}(\epsilon, \tau)$ diverges as $\tau \rightarrow 0^+$ for every $\epsilon > 0$, then $i\omega$ is an element of the spectrum of V .
- If $\lim_{\tau \rightarrow 0^+} \omega_\tau =: \omega$ exists, and $\mathcal{D}(\tilde{z}_\tau)$ is bounded as $\tau \rightarrow 0^+$, then $i\omega$ is an eigenvalue of V . Moreover, the sequence \tilde{z}_τ converges to the eigenspace of V corresponding to $i\omega$.

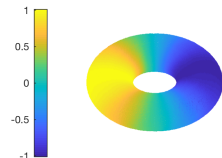
Torus rotation—spectra of W_T



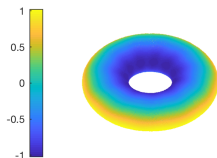
- $\mathcal{M} = M = X = \mathbb{T}^2$
- $\Phi^t : (\theta^1, \theta^2) \mapsto (\theta^1 + t, \theta^2 + \alpha t)$
- $\alpha = \sqrt{30}$

Torus rotation—eigenfunctions of W_T

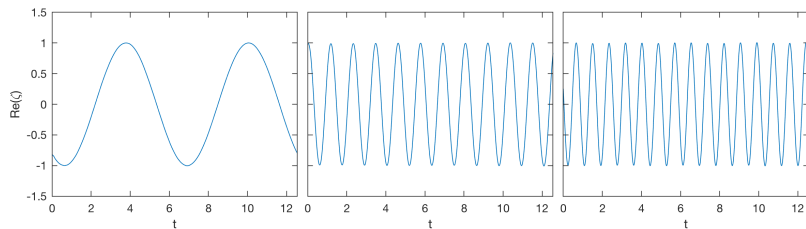
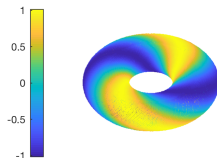
$\zeta_1, \omega_1 = 1.000, D(\zeta_1) = 0.043$



$\zeta_5, \omega_5 = 5.473, D(\zeta_5) = 0.141$



$\zeta_9, \omega_9 = 7.466, D(\zeta_9) = 0.250$



Data-driven modeling scenario

Consider that a **time-ordered dataset** $F(x_0), \dots, F(x_{N-1})$, $x_n = \Phi^{n\Delta t}(x_0)$, is available, s.t.

- $F : M \rightarrow Y$ is a C^1 , injective map into a manifold Y
- μ is an ergodic invariant measure of $\Phi^{\Delta t}$
- x_0 lies in the **basin** of μ ; i.e., as $N \rightarrow \infty$, the sampling measures μ_N weak-converge to μ :

$$\lim_{N \rightarrow \infty} \int_M f d\mu_N = \int_M f d\mu, \quad \forall f \in C^0(M), \quad \mu_N = \frac{1}{N} \sum_{n=0}^{N-1} \delta_{x_n}$$

- x_0 is not a fixed point

Approximating the kernel integral operators

- Replace $L^2(\mu)$ by $L^2(\mu_N)$
- Construct a $L^2(\mu_N)$ -strictly positive, C^1 , Markov ergodic kernel $\rho_N : M \times M \rightarrow \mathbb{R}$ as a **pullback kernel** from the data space Y :

$$\rho_N(x, y) = \rho_N(F(x), F(y))$$

- Let \mathcal{H}_N be the RKHS on M associated with ρ_N ; define $P_N : L^2(\mu_N) \rightarrow \mathcal{H}_N$ and $\mathcal{H}_{N,\tau}$ as in the case of μ
- Under mild assumptions, as $N \rightarrow \infty$, $\rho_N \rightarrow \rho$ in $C^0(M \times M)$ (G. et al. 2017), and the corresponding kernel integral operators on $C^0(M)$ converge **collectively compactly** (Von Luxburg et al. 2008)
- As a result, for every eigenvalue $\lambda_j > 0$ of $G = P^*P$, $\lambda_{j,N}$ converges to λ_j , where $\lambda_{j,N}$ are eigenvalues of $G_N = P_N^*P_N$
- For every eigenfunction $\phi_j \in L^2(\mu)$ corresponding to $\lambda_j > 0$, there exist eigenfunctions $\phi_{j,N} \in L^2(\mu_N)$ of $G_N = P_N^*P_N$ corresponding to $\lambda_{j,N}$ whose continuous representatives, $\varphi_{j,N}$, converge in $C^0(M)$ to the continuous representative φ_j of ϕ_j :

$$\varphi_{j,N}(x) = \frac{1}{\lambda_{j,N}} \int_M \rho_N(x, y) \phi_{j,N}(y) d\mu_N(y), \quad \varphi_j(x) = \frac{1}{\lambda_j} \int_M \rho(x, y) \phi_j(y) d\mu(y)$$

Approximating the evolution operators

- Replace the Koopman operator $U^t : f \mapsto f \circ \Phi^t$ on $L^2(\mu)$ at $t = q \Delta t$, $q \in \mathbb{N}_0$, by the **shift operator** $U_N^{(q)} : L^2(\mu_N) \rightarrow L^2(\mu_N)$,

$$U_N^{(q)} f(x_n) = \begin{cases} f(x_{n+q}), & 0 \leq n \leq N-1-q, \\ 0, & \text{otherwise} \end{cases}$$

- Replace the generator V by a **skew-adjoint, finite-difference operator** $V_{N,\Delta t} : L^2(\mu_N) \rightarrow L^2(\mu_N)$, e.g.,

$$V_{N,\Delta t} = \frac{\tilde{V}_{N,\Delta t} - \tilde{V}_{N,\Delta t}^*}{2}, \quad \tilde{V}_{N,\Delta t} f(x_n) = \begin{cases} \frac{f(x_n) - f(x_{n-1})}{\Delta t}, & 1 \leq n \leq N-1, \\ 0, & \text{otherwise} \end{cases}$$

- Introduce the orthogonal projections $\Pi_{\tau,N,L} : \mathcal{H}_{\tau,N} \rightarrow \mathcal{H}_{\tau,N}$ mapping into $\text{span}\{\psi_{0,\tau,N}, \dots, \psi_{L-1,\tau,N}\}$
- Replace $W_\tau : \mathcal{H}_\tau \rightarrow \mathcal{H}_\tau$ by the skew-adjoint operator $W_{\tau,N,\Delta t,L}$ on $\mathcal{H}_{\tau,N}$,

$$W_{\tau,N,\Delta t,L} = \Pi_{\tau,N,L} P_{\tau,N}^* V_{N,\Delta t} P_{\tau,N} \Pi_{\tau,N,L}$$

- Solve the eigenproblem for $W_{\tau,N,\Delta t,L}$:

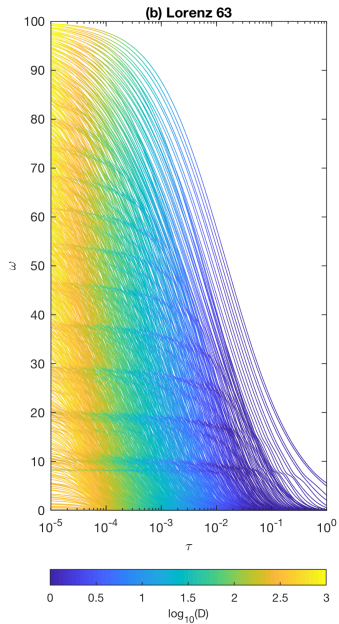
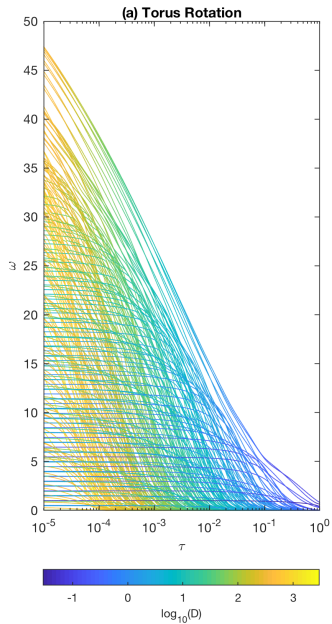
$$W_{\tau,N,\Delta t,L} \zeta_j^{(\tau,N,\Delta t,L)} = i\omega_j^{(\tau,N,\Delta t,L)} \zeta_j^{(\tau,N,\Delta t,L)}$$

- Functional calculus for $W_{\tau,N,\Delta t,L}$ constructed analogously to W_τ

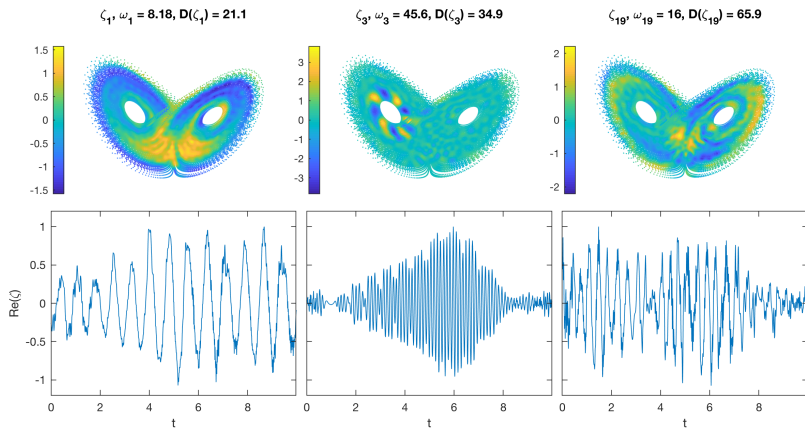
Convergence of the data-driven schemes

- Introduce the orthogonal projections $\Pi_{\tau,L} : \mathcal{H}_\tau \rightarrow \mathcal{H}_\tau$ mapping into $\text{span}\{\psi_{0,\tau}, \dots, \psi_{L-1,\tau}\}$, and define the finite-rank operator $W_{\tau,L} \equiv \Pi_{L,\tau} W_\tau \Pi_{L,\tau}$
- At fixed L and as $\Delta t \rightarrow 0$, $N \rightarrow \infty$ (in that order), the eigenvalues $i\omega_j^{(\tau,N,\Delta t,L)}$ converge to the eigenvalues $i\omega_j^{(\tau,L)}$ of $W_{\tau,L}$, and the corresponding eigenfunctions converge in $C^0(M)$ norm
- At fixed τ and as $L \rightarrow \infty$, the eigenvalues $i\omega_j^{(\tau,L)}$ converge to the eigenvalues $i\omega_j^{(\tau)}$ of W_τ , and the corresponding eigenfunctions converge in \mathcal{H}_τ norm
- For every $i\omega \in \sigma(V)$, there exists a continuous curve of eigenvalues of W_τ converging to it as $\tau \rightarrow 0^+$; moreover, for every bounded Borel-measurable set $\Omega \subset \mathbb{R}$ such that $E(\partial\Omega) = 0$, $P_\tau^* \mathcal{E}_\tau(\Omega) \mathcal{N}_\tau$ converges strongly to $E(\Omega)$
- In summary, **spectral convergence** of $W_{\tau,N,\Delta t,L}$ to V is to be understood in a joint limit of $N \rightarrow \infty$, $\Delta t \rightarrow 0$, $L \rightarrow \infty$, $\tau \rightarrow 0^+$ (in that order)

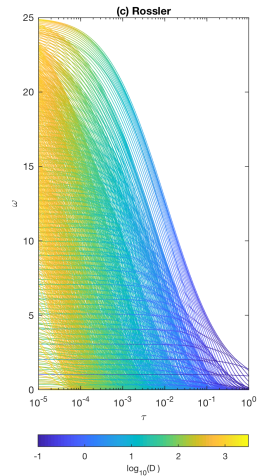
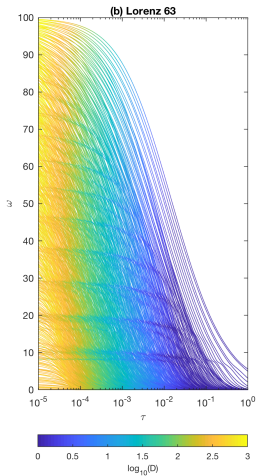
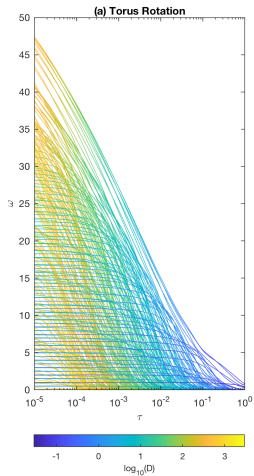
Lorenz 63 system—spectra of W_τ



L63 system—eigenfunctions of W_T

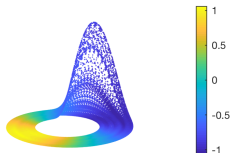


Rössler system—spectra of W_τ

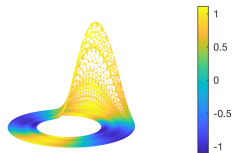


Rössler system—eigenfunctions of W_T

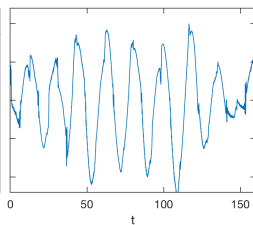
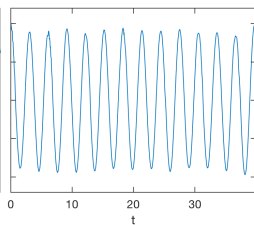
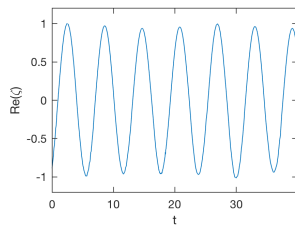
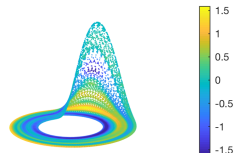
$\zeta_1, \omega_1 = 1.03, D(\zeta_1) = 0.608$



$\zeta_3, \omega_3 = 2.05, D(\zeta_3) = 1.44$



$\zeta_{39}, \omega_{39} = 0.355, D(\zeta_{39}) = 75.3$

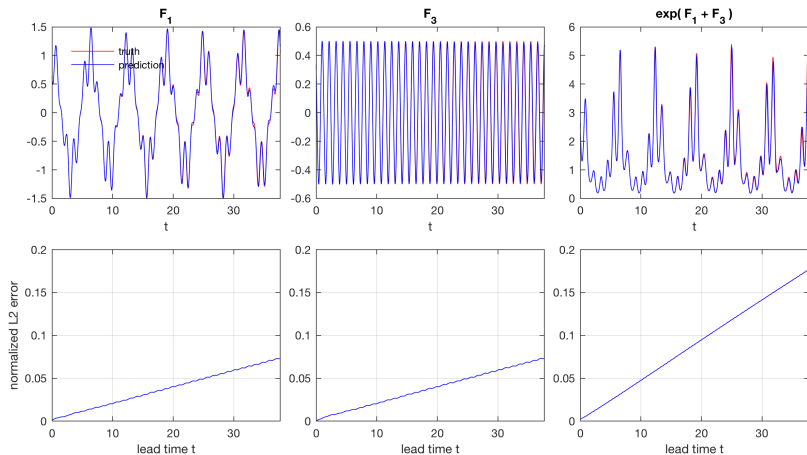


Prediction of observables

- For every $\tau > 0$, W_τ generates a **norm-continuous** group of unitary operators $e^{tW_\tau} : \mathcal{H}_\tau \rightarrow \mathcal{H}_\tau$, $t \in \mathbb{R}$, approximating U^t
- For any observable $f \in L^2(\mu)$, error bound $\epsilon > 0$, and compact set $\mathcal{T} \subset \mathbb{R}$, there exists $\hat{f}_\epsilon \in \cap_{\tau > 0} \mathcal{H}_\tau$ (independent of \mathcal{T}) and $\tau_0 > 0$, such that for every $\tau \in (0, \tau_0)$ and $t \in \mathcal{T}$,

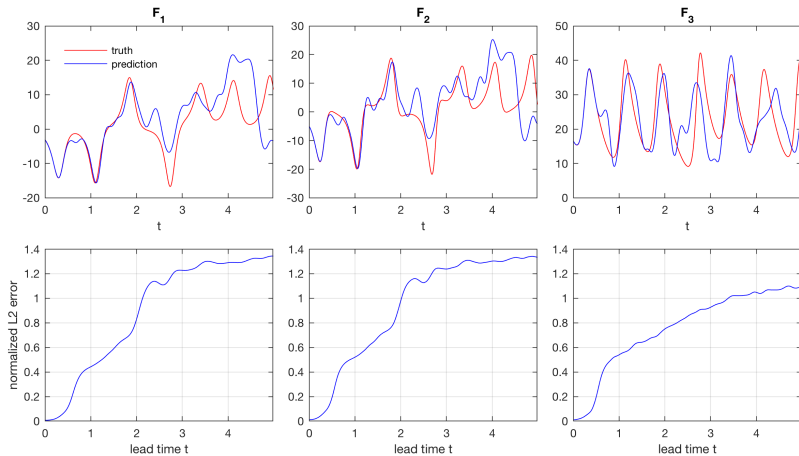
$$\left\| U^t f - P_\tau^* e^{tW_\tau} f_\epsilon \right\|_{L^2(\mu)} < \epsilon, \quad e^{tW_\tau} f_\epsilon = \sum_{j=0}^{\infty} e^{ti\omega_{\tau,j}} \langle \zeta_{\tau,j}, f_\epsilon \rangle_{\mathcal{H}_\tau} \zeta_{\tau,j}$$

Torus rotation—prediction of observables using e^{tW_T}



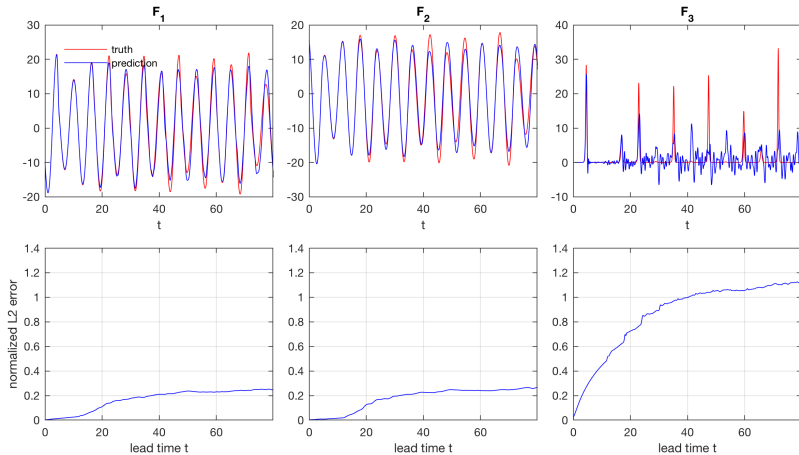
$$F : \mathbb{T}^2 \rightarrow \mathbb{R}^3, \quad (\theta_1, \theta_2) \mapsto \begin{pmatrix} (1 + R \cos \theta_2) \cos \theta_1 \\ (1 + R \cos \theta_2) \sin \theta_1 \\ \sin \theta_2 \end{pmatrix}$$

L63 system—prediction of observables using e^{tW_τ}



$$F : \mathbb{R}^3 \rightarrow \mathbb{R}^3, \quad F = I$$

Rössler system—prediction of observables using e^{tW_τ}

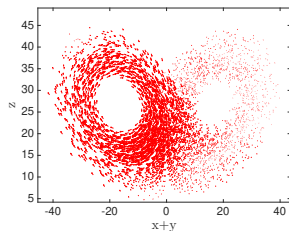


$$F : \mathbb{R}^3 \rightarrow \mathbb{R}^3, \quad F = I$$

Conclusions

- Kernel methods provide a useful framework for data-driven prediction and spectral decomposition in ergodic dynamical systems
- Advantages of the approach include the ability to construct bases for function spaces of appropriate regularity with minimal prior knowledge about the system
- Regularization approach based on compactification of the generator in a space of functions of high regularity (RKHS), as opposed to adding diffusion, leads to a notion of coherent observables in systems with continuous spectra and an approximation framework for the functional calculus of the generator

Ongoing and future work:



- Data assimilation and control
- Spectral approximation of vector fields and differential forms (exterior calculus)
(Berry & G. 2018)
- Applications to climate and fluid dynamics

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