

How well can one resolve the state space of a chaotic flow?

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Outline

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 - intuition
 - idea #1: partition by periodic points
 - strategy
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 - idea #2: evolve densities, not Langevin trajectories
 - idea #3: for unstable directions, look back
- 3 optimal partition hypothesis**
 - idea #4: finite-dimensional Fokker-Planck matrices
- 4 conclusions, open questions**
 - literature

dynamical theory of turbulence?

dynamics of high-dimensional flows - open questions

is the dynamics like what we know from low dimensional systems?

describe the attracting 'inertial manifold' for Navier-Stokes?

Ruelle / Gutzwiller periodic orbit theory?

deterministic chaos vs. noise

any physical system:

noise limits the resolution that can be attained in partitioning the state space

chaotic flow: noisy orbits

deterministic: 1-dimensional trajectories

probabilistic: peaked densities smeared out by the noise

noisy orbits

probabilistic densities smeared out by the noise:

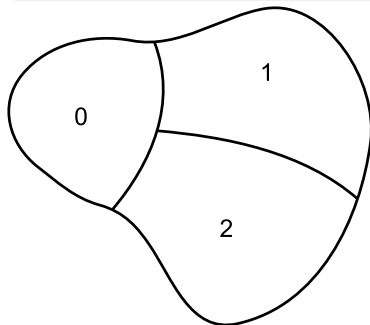
a finite # fits into the attractor

goal: determine

the **finest attainable** partition

deterministic partition

state space coarse partition

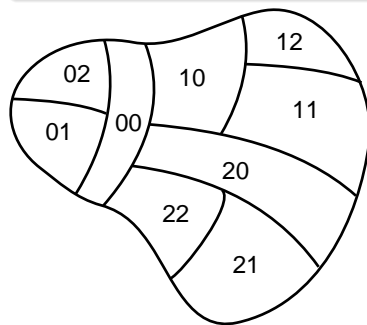


$$\mathcal{M} = \mathcal{M}_0 \cup \mathcal{M}_1 \cup \mathcal{M}_2$$

ternary alphabet

$$\mathcal{A} = \{1, 2, 3\}.$$

1-step memory refinement

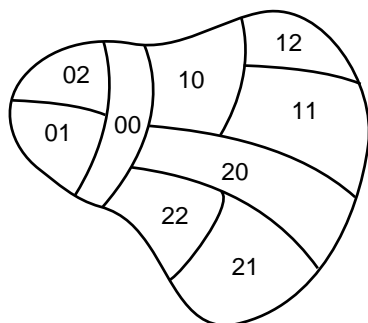


$$\mathcal{M}_i = \mathcal{M}_{i0} \cup \mathcal{M}_{i1} \cup \mathcal{M}_{i2}$$

labeled by nine 'words'

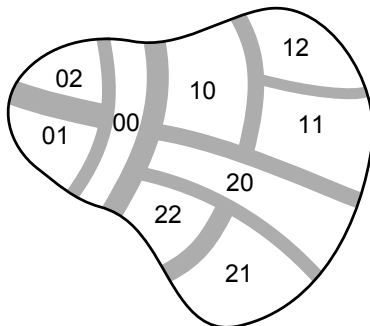
$$\{00, 01, 02, \dots, 21, 22\}.$$

deterministic vs. noisy partitions



deterministic partition

can be refined
ad infinitum



noise blurs the boundaries

when overlapping, no further
refinement of partition

idea #1: partition by periodic points

periodic points instead of boundaries

- mhm, do not know how to compute boundaries...
- however, each partition contains a short periodic point smeared into a 'cigar' by noise

idea #1: partition by periodic points

periodic points instead of boundaries

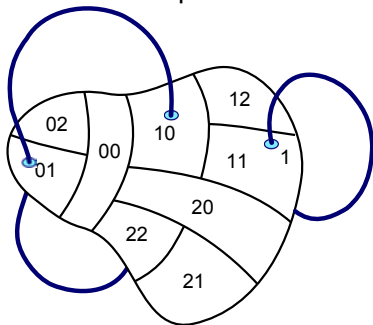
- each partition contains a short periodic point smeared into a 'cigar' by noise

compute the size of a noisy periodic point neighborhood!

idea #1: partition by periodic points

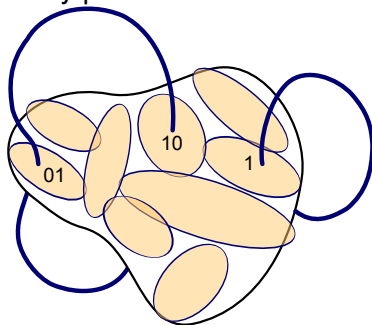
periodic orbit partition

deterministic partition



some short periodic points:
 fixed point $\bar{1} = \{x_1\}$
 two-cycle $\overline{01} = \{x_{01}, x_{10}\}$

noisy partition



periodic points blurred by the
 Langevin noise into
 cigar-shaped densities

- successive refinements of a deterministic partition: exponentially shrinking neighborhoods
- as the periods of periodic orbits increase, the diffusion always wins:

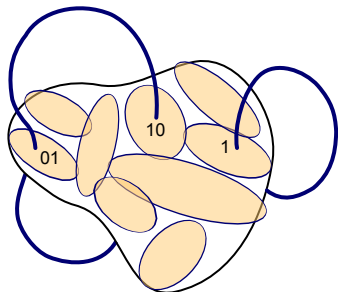
partition stops at the finest attainable partition, beyond which the diffusive smearing exceeds the size of any deterministic subpartition.

- the local diffusion rate differs from a trajectory to a trajectory, as different neighborhoods merge at different times, so

there is *no one single time* beyond which noise takes over

idea #1: partition by periodic points

noisy periodic orbit partition



optimal partition hypothesis

optimal partition:
the maximal set of resolvable
periodic point neighborhoods

why care?

if the high-dimensional flow has only a few unstable directions, the overlapping stochastic 'cigars' provide a *compact cover* of the noisy chaotic attractor, embedded in a state space of arbitrarily high dimension

strategy

- use periodic orbits to partition state space
- compute local eigenfunctions of the Fokker-Planck operator to determine their neighborhoods
- done once neighborhoods overlap

idea #2: evolve densities, not Langevin trajectories

how big is the neighborhood blurred by the Langevin noise?

next, derive **the** (well known) **key formula**

composition law for the covariance matrix Q_a

of a linearly evolved Gaussian density,

$$Q_{a+1} = M_a Q_a M_a^T + \Delta_a$$

density covariance matrix at time a : Q_a

Langevin noise covariance matrix: Δ_a

Jacobian matrix of linearized flow: M_a

idea #2: evolve densities, not Langevin trajectories

derivation

keep things simple: illustrate by

***d*-dimensional discrete time stochastic flow**

$$x' = f(x) + \xi_a$$

uncorrelated in time

$$\langle \xi_a \rangle = 0, \quad \langle \xi_a \cdot \xi_b \rangle = 2 d D \delta_{ab}$$

[all results apply both to the continuous and discrete time flows]

idea #2: evolve densities, not Langevin trajectories

standard normal (Gaussian) probability distribution

d-dimensional *discrete time* stochastic flow

$$x' = f(x) + \xi_a$$

1-time step evolution = probability of reaching x' given random kick, Gaussian distributed $\xi_a = x' - f(x)$

$$\frac{1}{\sqrt{4\pi D}} \exp\left(-\frac{\xi_a^2}{4D}\right)$$

variance $2D$, standard deviation $\sqrt{2D}$

idea #2: evolve densities, not Langevin trajectories

local Fokker-Planck operator

let

$$\{\dots, X_{-1}, X_0, X_1, X_2, \dots\}$$

be a deterministic trajectory

$$X_{a+1} = f(X_a)$$

noisy trajectory is centered on the deterministic trajectory

$$X = X_a + Z_a, \quad f_a(Z_a) = f(X_a + Z_a) - X_{a+1}$$

local Fokker-Planck operator

$$\mathcal{L}_a(z_{a+1}, z_a) = \frac{1}{\sqrt{4\pi D}} \exp \left[-\frac{(z_{a+1} - f_a(z_a))^2}{4D} \right]$$

Fokker-Planck formulation replaces individual noisy trajectories by evolution of their densities

$$\mathcal{L}^k(z_k, z_0) = \int [dz] e^{-\frac{1}{2} \sum_a (z_{a+1} - f_a(z_a))^T \frac{1}{\Delta} (z_{a+1} - f_a(z_a))}$$

evolution to time k is given by the d -dimensional path integral over the $k-1$ intermediate noisy trajectory points

$$\mathcal{L}^k(z_k, z_0) = \int [dz] e^{-\frac{1}{2} \sum_a (z_{a+1} - f_a(z_a))^T \frac{1}{\Delta} (z_{a+1} - f_a(z_a))}$$

zero mean; covariance matrix / diffusion tensor Δ

$$\langle \xi_j(t_a) \rangle = 0, \quad \langle \xi_{a,i} \xi_{a,j}^T \rangle = \Delta_{ij},$$

where $\langle \dots \rangle$ stands for ensemble average over many realizations of the noise

map $f(x_a)$ is nonlinear. Taylor expand

$$f_a(z_a) = M_a z_a + \dots$$

approximate the noisy map by its linearized action,

$$z_{a+1} = M_a z_a + \xi_a,$$

where M_a is the Jacobian matrix, $(M_a)_{ij} = \partial f(x_a)_i / \partial x_j$

idea #2: evolve densities, not Langevin trajectories

M_a is the Jacobian matrix, $(M_a)_{ij} = \partial f(x_a)_i / \partial x_j$

linearized Fokker-Planck operator

$$\mathcal{L}_a(z_{a+1}, z_a) = \frac{1}{N} e^{-\frac{1}{2}(z_{a+1} - M_a z_a)^T \frac{1}{\Delta} (z_{a+1} - M_a z_a)}$$

[Kalman filter 'prediction', WKB, semiclassical, saddlepoint, ... approximation]

linearized evolution operator maps a cigar-shaped Gaussian density distribution with covariance matrix Q_a at time a

$$\rho_a(z_a) = \frac{1}{C_a} e^{-\frac{1}{2} z_a^T \frac{1}{Q_a} z_a}$$

into cigar

$$\rho_{a+1}(z_{a+1}) = \int dz_a \mathcal{L}_a(z_{a+1}, z_a) \rho_a(z_a)$$

one time step later

idea #2: evolve densities, not Langevin trajectories

rolled your own cigar

convolution of a Gaussian with a Gaussian is again a Gaussian. Integrate, obtain that

the covariance of the transported packet is given by

evolution law for the covariance matrix Q_a

$$Q_{a+1} = M_a Q_a M_a^T + \Delta_a$$

idea #2: evolve densities, not Langevin trajectories

rolled your own cigar

evolution law for the covariance matrix Q_a

$$Q_{a+1} = M_a Q_a M_a^T + \Delta_a$$

in one time step a Gaussian density distribution with covariance matrix Q_a is smeared into a Gaussian 'cigar' whose widths and orientation are given by eigenvalues and eigenvectors of Q_{a+1}

- (1) deterministically transported and deformed
local density covariance matrix $Q \rightarrow MQM^T$, and
- (2) and noise covariance matrix Δ

add up as sums of squares

idea #2: evolve densities, not Langevin trajectories

noise along a trajectory

iterate $Q_{a+1} = M_a Q_a M_a^T + \Delta_a$ along the trajectory

if M is contracting, over time the memory of the covariance Q_{a-n} of the starting density is lost, with iteration leading to the limit distribution

$$Q_a = \Delta_a + M_{a-1} \Delta_{a-1} M_{a-1}^T + M_{a-2}^2 \Delta_{a-2} (M_{a-2}^2)^T + \dots$$

diffusive dynamics of a nonlinear system is fundamentally different from Brownian motion, as the flow induces a history dependent effective noise. **Always**

idea #2: evolve densities, not Langevin trajectories

noise and a single attractive fixed point

if all eigenvalues of M are strictly contracting, any initial compact measure converges to the unique invariant Gaussian measure $\rho_0(z)$ whose covariance matrix satisfies

time-invariant measure condition

$$Q = MQM^T + \Delta$$

idea #2: evolve densities, not Langevin trajectories

solving for stationary covariance Q

assume that $[d \times d]$ matrix M has only nonzero eigenvalues $\{\Lambda_j\}$ and d linearly independent right and left eigenvectors (M is not defective)

$$M \mathbf{e}^{(j)} = \Lambda_j \mathbf{e}^{(j)}, \quad \mathbf{e}_{(j)} M = \Lambda_j \mathbf{e}_{(j)}$$

eigenvectors can always be rescaled so that they are mutually orthogonal

$$\mathbf{e}_{(j)} \cdot \mathbf{e}^{(k)} = \delta_{jk}$$

idea #2: evolve densities, not Langevin trajectories

form from the d column eigenvectors a $[d \times d]$ matrix

$$S = [\mathbf{e}^{(1)}, \mathbf{e}^{(2)}, \dots, \mathbf{e}^{(d)}], \quad MS = \Lambda S$$

by $\mathbf{e}^{(j)} \cdot \mathbf{e}^{(k)} = \delta_{jk}$, the matrix whose rows are left eigenvectors is then the inverse

$$S^{-1} = [\mathbf{e}_{(1)}, \mathbf{e}_{(2)}, \dots, \mathbf{e}_{(d)}]^T$$

S diagonalizes M and its transpose M^T by

similarity transformation

$$S^{-1}MS = \Lambda, \quad S^T M^T (S^{-1})^T = \Lambda$$

idea #2: evolve densities, not Langevin trajectories

define $\hat{Q} = S^{-1}Q(S^{-1})^T$ and $\hat{\Delta} = S^{-1}\Delta(S^{-1})^T$

time-invariant measure condition $Q = MQM^T + \Delta$ now takes form

$$\hat{Q} - \Lambda\hat{Q}\Lambda = \hat{\Delta}$$

matrix elements are $\hat{Q}_{ij}(1 - \Lambda_i\Lambda_j) = \hat{\Delta}_{ij}$, so

$$\hat{Q}_{ij} = \frac{\hat{\Delta}_{ij}}{1 - \Lambda_i\Lambda_j}$$

and the attracting fixed point covariance matrix is given by

$$Q = S\hat{Q}S^T$$

note!

covariance matrix

$$\hat{Q}_{ij} = \frac{\hat{\Delta}_{ij}}{1 - \Lambda_i \Lambda_j}$$

elements must be strictly positive

true only if all Floquet multipliers (Jacobian matrix M eigenvalues) are contracting, $|\Lambda_j| < 1$

idea #2: evolve densities, not Langevin trajectories

summary: covariance matrix Q for an attractive fixed point

- determine the Jacobian matrix M eigenvalues and eigenvectors

$$M \mathbf{e}^{(j)} = \Lambda_j \mathbf{e}^{(j)}$$

- go to coordinate frame where M is diagonal,

$$S^{-1}MS = \Lambda, \quad \hat{Q} = S^{-1}Q(S^{-1})^T, \quad \hat{\Delta} = S^{-1}\Delta(S^{-1})^T$$

- evaluate

$$\hat{Q}_{ij} = \frac{\hat{\Delta}_{ij}}{1 - \Lambda_i \Lambda_j}$$

- go back to the original coordinates

$$Q = S\hat{Q}S^T$$

a numerical diagonalization of the covariance matrix

$Q = S\hat{Q}S^T$ yields the principal axis of the equilibrium Gaussian 'cigar'

eigenvectors of Q (it is a symmetric matrix) are orthogonal and have orientations **distinct** from the left/right eigenvectors of the non-normal Jacobian matrix M

idea #2: evolve densities, not Langevin trajectories

example : Ornstein-Uhlenbeck process

contracting noisy 1-dimensional map

$$z_{n+1} = \Lambda z_n + \xi_n, \quad |\Lambda| < 1$$

width of the natural measure concentrated at the deterministic fixed point $z = 0$

$$Q = \frac{2D}{1 - |\Lambda|^2}, \quad \rho_0(z) = \frac{1}{\sqrt{2\pi Q}} \exp\left(-\frac{z^2}{2Q}\right),$$

idea #2: evolve densities, not Langevin trajectories

example : Ornstein-Uhlenbeck process

width of the natural measure concentrated at the deterministic fixed point $z = 0$

$$Q = \frac{2D}{1 - |\Lambda|^2}, \quad \rho_0(z) = \frac{1}{\sqrt{2\pi Q}} \exp\left(-\frac{z^2}{2Q}\right),$$

- is balance between contraction by Λ and diffusive smearing by $2D$ at each time step
- for strongly contracting Λ , the width is due to the noise only
- As $|\Lambda| \rightarrow 1$ the width diverges: the trajectories are no longer confined, but diffuse by Brownian motion

idea #3: for unstable directions, look back

things fall apart, centre cannot hold

but what if M has *expanding* Floquet multipliers?

both deterministic dynamics and noise tend to smear densities away from the fixed point: no peaked Gaussian in your future

idea #3: for unstable directions, look back

things fall apart, centre cannot hold

but what if M has *expanding* Floquet multipliers?

Fokker-Planck operator is non-selfadjoint

If right eigenvector is peaked (attracting fixed point)
the left eigenvector is flat (probability conservation)

idea #3: for unstable directions, look back

adjoint Fokker-Planck operator

to estimate the size of a noisy neighborhood of a trajectory point x_a along its *unstable* directions, we need to determine the effect of noise on the points *preceding* x_a

this is described by the *adjoint Fokker-Planck operator*

$$\begin{aligned}\tilde{\rho}(y, k-1) &= \mathcal{L}^\dagger \circ \tilde{\rho}(y, k) \\ &= \int [dy] \exp \left\{ -\frac{1}{2} (y - f(x))^T \frac{1}{\Delta} (y - f(x)) \right\} \tilde{\rho}(y, k),\end{aligned}$$

carries a density concentrated around the previous point x_{n-1} to a density concentrated around x_n

idea #3: for unstable directions, look back

case of *repelling* fixed point

if M has only *expanding* Floquet multipliers, both deterministic dynamics and noise tend to smear densities away from the fixed point

balance between the two is described by the *adjoint Fokker-Planck operator*, and the evolution of the covariance matrix Q is now given by

$$Q_a + \Delta = M_a Q_{a+1} M_a^T,$$

idea #3: for unstable directions, look back

what about the hyperbolic, expanding and contracting case?

the future (if all Floquet multipliers are contracting, $|\Lambda_j| < 1$):

$$Q_{ij} = S_{ik} \frac{\hat{\Delta}_{jl}}{1 - \Lambda_k \Lambda_l} S_{lj}^T$$

blast from the past (if all Floquet multipliers are expanding, $|\Lambda_j| > 1$):

$$Q_{ij} = S_{ik} \frac{\hat{\Delta}_{jl}}{\Lambda_k \Lambda_l - 1} S_{lj}^T$$

question to you:

what is the relation between contracting / expanding Floquet eigenvectors $\{\mathbf{e}^{(j)}\}$ and the semiaxes of ellipsoid

$$Q_{ij} = S_{ik} \frac{\hat{\Delta}_{jl}}{1 - \Lambda_k \Lambda_l} S_{lj}^T ?$$

optimal partition challenge

finally in position to address our challenge:

determine the finest possible partition for a given noise

does it work?

evaluation of these Gaussian densities requires no Fokker-Planck PDE formalism

width of a Gaussian packet centered on a trajectory is fully specified by a deterministic computation that is already a pre-computed byproduct of the periodic orbit computations: the deterministic orbit and its linear stability

resolution of a one-dimensional chaotic repeller

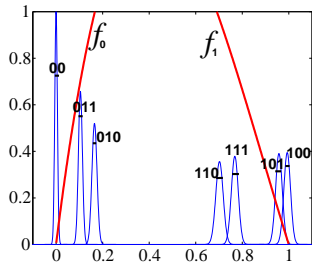
As an illustration of the method, consider the chaotic repeller on the unit interval

$$x_{n+1} = \Lambda_0 x_n(1 - x_n)(1 - bx_n) + \xi_n, \quad \Lambda_0 = 8, \quad b = 0.6,$$

with noise strength $2D = 0.002$

optimal partition, 1 dimensional map

f_0, f_1 : branches of deterministic map
 a deterministic orbit itinerary is given
 by the $\{f_0, f_1\}$ branches visitation
 sequence



[symbolic dynamics, however, is not a prerequisite for
 implementing the method]

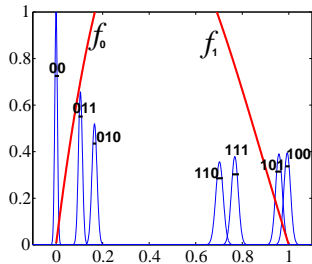
'the best possible of all partitions' hypothesis formulated as an algorithm

- calculate the local adjoint Fokker-Planck operator eigenfunction width Q_a for every unstable periodic point x_a
- assign one-standard deviation neighborhood $[x_a - Q_a, x_a + Q_a]$ to every unstable periodic point x_a
- cover the state space with neighborhoods of orbit points of higher and higher period n_p
- stop refining the local resolution whenever the adjacent neighborhoods of x_a and x_b overlap:

$$|x_a - x_b| < Q_a + Q_b$$

optimal partition, 1 dimensional map

f_0, f_1 : branches of deterministic map
 local eigenfunctions $\tilde{\rho}_a$ partition state space by neighborhoods of periodic points of period 3
 neighborhoods \mathcal{M}_{000} and \mathcal{M}_{001} overlap, so \mathcal{M}_{00} cannot be resolved further



all neighborhoods $\{\mathcal{M}_{0101}, \mathcal{M}_{0100}, \dots\}$ of period $n_p = 4$ cycle points overlap, so

state space can be resolved into 7 neighborhoods

$$\{\mathcal{M}_{00}, \mathcal{M}_{011}, \mathcal{M}_{010}, \mathcal{M}_{110}, \mathcal{M}_{111}, \mathcal{M}_{101}, \mathcal{M}_{100}\}$$

idea #4: finite-dimensional Fokker-Planck matrices

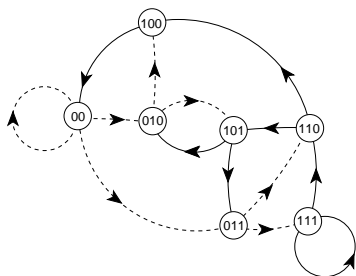
Markov partition

evolution in time maps intervals

$$\mathcal{M}_{011} \rightarrow \{\mathcal{M}_{110}, \mathcal{M}_{111}\}$$

$$\mathcal{M}_{00} \rightarrow \{\mathcal{M}_{00}, \mathcal{M}_{011}, \mathcal{M}_{010}\}, \text{ etc..}$$

summarized by the transition graph (links correspond to elements of transition matrix T_{ba}): the regions b that can be reached from the region a in one time step



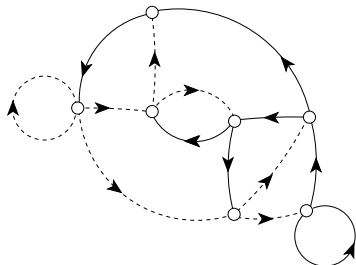
transition graph

7 nodes = 7 regions of the optimal partition

dotted links = symbol 0 (next region reached by f_0)

full links = symbol 1 (next region reached by f_1)

region labels in the nodes can be omitted, with links keeping track of the symbolic dynamics



- (1) deterministic dynamics is full binary shift, but
- (2) noise dynamics nontrivial and *finite*

idea #4: finite-dimensional Fokker-Planck matrices

predictions

escape rate and the Lyapunov exponent of the repeller

are given by the leading eigenvalue of this $[7 \times 7]$ graph / transition matrix

tests : numerical results are consistent with the full Fokker-Planck PDE simulations

what is novel?

- we have shown how to compute the **locally optimal partition**, for a given dynamical system and given noise, in terms of local eigenfunctions of the forward-backward actions of the Fokker-Planck operator and its adjoint

what is novel?

- **A handsome reward:** as the optimal partition is always finite, the dynamics on this 'best possible of all partitions' is encoded by a finite transition graph of finite memory, and the Fokker-Planck operator can be represented by a finite matrix

the payback

claim:

optimal partition hypothesis

- the best of all possible state space partitions
- optimal for the given noise

the payback

claim:

optimal partition hypothesis

- optimal partition replaces stochastic PDEs by finite, low-dimensional Fokker-Planck matrices

the payback

claim:

optimal partition hypothesis

- optimal partition replaces stochastic PDEs by finite, low-dimensional Fokker-Planck matrices
- finite matrix calculations, finite cycle expansions \Rightarrow optimal estimates of long-time observables (escape rates, Lyapunov exponents, etc.)

questions?

- how to combine Fokker-Planck and adjoint Fokker-Planck operators to describe hyperbolic periodic points (saddles)?

questions?

- how to combine Fokker-Planck and adjoint Fokker-Planck operators to describe hyperbolic periodic points (saddles)?
Hint: H. H. Rugh (1992)? combined deterministic evolution operator and adjoint operators to describe hyperbolic periodic points (saddles)

questions?

- apply to Navier-Stokes turbulence?

computation of unstable periodic orbits in high-dimensional state spaces, such as Navier-Stokes, is at the border of what is feasible numerically, and criteria to identify finite sets of the most important solutions are very much needed. Where are we to stop calculating orbits of a given hyperbolic flow?

references

- D. Lippolis and P. Cvitanović, *How well can one resolve the state space of a chaotic map?*, Phys. Rev. Lett. 104, 014101 (2010); [arXiv.org:0902.4269](https://arxiv.org/abs/0902.4269)
- D. Lippolis and P. Cvitanović, *Optimal resolution of the state space of a chaotic flow in presence of noise (in preparation)*

the rest is noise

brief history of noise

literature on stochastic dynamical systems is vast, starts with the Laplace 1810 memoir

all of this literature assumes uniform / bounded hyperbolicity and seeks to define a single, globally averaged diffusion induced average resolution (Heisenberg time, in the context of semi-classical quantization).

brief history of noise cost function

appears to have been first introduced by Wiener as the exact solution for a purely diffusive Wiener-Lévy process in one dimension.

Onsager and Machlup use it in their variational principle to study thermodynamic fluctuations in a neighborhood of single, linearly attractive equilibrium point (i.e., without any dynamics).

brief history of noise

dynamical 'action' Lagrangian, and symplectic noise Hamiltonian were first written down by Freidlin and Wentzell (1970's), whose formulation of the 'large deviation principle' was inspired by the Feynman quantum path integral (1940's). Feynman, in turn, followed Dirac (1933's) who was the first to discover that in the short-time limit the quantum propagator (imaginary time, quantum sibling of the Wiener stochastic distribution) is exact. Gaspard: 'pseudo-energy of the Onsager-Machlup-Freidlin-Wentzell scheme.' Roncadelli: the 'Wiener-Onsager-Machlup Lagrangian.'

Langevin flow

here we briefly repeat the derivation of local Fokker-Planck operator for a continuous time flow

d -dimensional stochastic flow

$$\frac{dx}{dt} = v(x) + \hat{\xi}(t),$$

deterministic velocity field $v(x)$, called 'drift' in the stochastic literature

density evolution

in time $\delta\tau$ the deterministic trajectory advances by $v(x_n) \delta\tau$.

the probability that the trajectory reaches x_{n+1}

$$\mathcal{L}^{\delta\tau}(x_{n+1}, x_n) = \frac{1}{N} \exp \left[-\frac{1}{2\delta\tau} \left(\xi_n^T \frac{1}{\Delta} \xi_n \right) \right].$$

density evolution

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ξ_n is the deviation of the noisy trajectory from the deterministic one,

$$\xi_n = \delta x_n - v(x_n) \delta\tau,$$

density evolution

the probability that the trajectory reaches x_{n+1}

$$\mathcal{L}^{\delta\tau}(x_{n+1}, x_n) = \frac{1}{N} \exp \left[-\frac{1}{2\delta\tau} (\xi_n^T \frac{1}{\Delta} \xi_n) \right].$$

ξ_n is the deviation of the noisy trajectory from the deterministic one,

$$\xi_n = \delta x_n - v(x_n) \delta\tau,$$

$$\delta x_n = x_{n+1} - x_n \simeq \dot{x}_n \delta\tau, \quad f^{\delta\tau}(x_n) - x_n \simeq v(x_n) \delta\tau,$$

density evolution

the probability that the trajectory reaches x_{n+1}

$$\mathcal{L}^{\delta\tau}(x_{n+1}, x_n) = \frac{1}{N} \exp \left[-\frac{1}{2\delta\tau} (\xi_n^T \frac{1}{\Delta} \xi_n) \right].$$

where

$$\{x_0, x_1, \dots, x_n, \dots, x_k\} = \{x(0), x(\delta\tau), \dots, x(n\delta\tau), \dots, x(t)\}$$

is a sequence of $k + 1$ points $x_n = x(t_n)$ along the noisy trajectory, separated by time increments $\delta\tau = t/k$

density evolution

finite time Fokker-Planck evolution $\rho(x, t) = \mathcal{L}^t \circ \rho(x, 0)$ of an initial density $\rho(x_0, 0)$ is obtained by a sequence of consecutive short-time steps

$$\mathcal{L}^t(x_k, x_0) = \int [dx] \exp \left\{ -\frac{1}{4D\delta\tau} \sum_{n=1}^{k-1} [x_{n+1} - f^{\delta\tau}(x_n)]^2 \right\},$$

probability distribution

standard normal

(Gaussian) probability distribution function,

$$\mathcal{L}^t(x, x_0) = \frac{1}{\sqrt{2\pi\sigma^2 t}} \exp \left[-\frac{(x - x_0)^2}{2\sigma^2 t} \right]$$

variance $\sigma^2 t = 2Dt$, standard deviation $\sqrt{2Dt}$
uncorrelated in time

$$\langle x_{n+1} - x_n \rangle = 0, \quad \langle (x_{m+1} - x_m)(x_{n+1} - x_n) \rangle = 2D \delta_{mn}$$

density evolution

in time $\delta\tau$ the deterministic trajectory advances by $v(x_n) \delta\tau$.

the probability that the trajectory reaches x_{n+1}

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$$\delta x_n = x_{n+1} - x_n \simeq \dot{x}_n \delta\tau, \quad f^{\delta\tau}(x_n) - x_n \simeq v(x_n) \delta\tau,$$

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where

$$\{x_0, x_1, \dots, x_n, \dots, x_k\} = \{x(0), x(\delta\tau), \dots, x(n\delta\tau), \dots, x(t)\}$$

is a sequence of $k + 1$ points $x_n = x(t_n)$ along the noisy trajectory, separated by time increments $\delta\tau = t/k$

zero mean and covariance matrix (diffusion tensor)

$$\langle \xi_j(t_n) \rangle = 0, \quad \langle \xi_i(t_m) \xi_j^T(t_n) \rangle = \Delta_{ij} \delta_{nm},$$

where $\langle \dots \rangle$ stands for ensemble average over many realizations of the noise.

density evolution

Fokker-Planck formulation replaces individual noisy trajectories by the evolution of their density

finite time Fokker-Planck evolution $\rho(x, t) = \mathcal{L}^t \circ \rho(x, 0)$ of an initial density $\rho(x_0, 0)$ is obtained by a sequence of consecutive short-time steps

$$\mathcal{L}^t(x_k, x_0) = \int [dx] \exp \left\{ -\frac{1}{4D\delta\tau} \sum_{n=1}^{k-1} [x_{n+1} - f^{\delta\tau}(x_n)]^2 \right\},$$

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continuous time limit, $\delta\tau = t/k \rightarrow 0$, defines the Fokker-Planck operator

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as a stochastic path (Wiener) integral

associated continuous time Fokker-Planck equation for the time evolution of a density of noisy trajectories is

$$\partial_t \rho(x, t) + \nabla \cdot (v(x)\rho(x, t)) = D \nabla^2 \rho(x, t).$$

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predictions

- finite partition \Rightarrow finite Fokker-Planck matrix
- its determinant yields time averages of dynamical observables

summary

- Computation of unstable periodic orbits in high-dimensional state spaces, such as Navier-Stokes, is at the border of what is feasible numerically, and criteria to identify finite sets of the most important solutions are very much needed. Where are we to stop calculating orbits of a given hyperbolic flow?

summary

- Intuitively, as we look at longer and longer periodic orbits, their neighborhoods shrink exponentially with time, while the variance of the noise-induced orbit smearing remains bounded; there has to be a *turnover time*, a time at which the noise-induced width overwhelms the exponentially shrinking deterministic dynamics, so that no better resolution is possible. Given a specified (possibly state space dependent) noise, we need to find, periodic orbit by periodic orbit, whether a further sub-partitioning is possible.

summary

- We have described here the *optimal partition hypothesis*, a new method for partitioning the state space of a chaotic repeller in presence of weak Gaussian noise, and tested the method in a 1-dimensional setting against direct numerical Fokker-Planck operator calculation.