

Central limit theorem for the measure of balls in non-conformal dynamics

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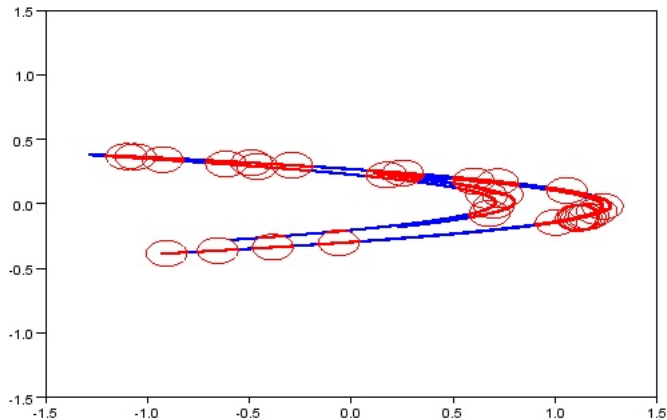
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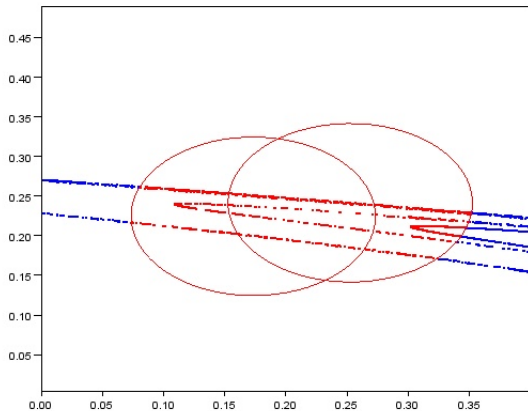
Outline

- 1 Fluctuations of the measure of balls
 - Introduction
 - Hausdorff and pointwise dimension of measures
 - The main theorem and its corollaries
- 2 Reduction to a non homogeneous sum of random variables
 - From balls to cylinders
 - Measure of the approximation as a Birkhoff sum
- 3 Probabilistic arguments
- 4 Generalizations and open questions
- 5 Application to Poincaré recurrence

How the measure behaves at small scales ?



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Motivation

For a smooth dynamical system and under suitable conditions, the **pointwise dimension** of an ergodic measure μ exists and is related to

- Hausdorff dimension
- entropy
- Lyapunov exponents

The existence of the pointwise dimension may be viewed as a **Law of Large Number**, it makes sense to ask for a **Central Limit Theorem** associated to it.

Some question related to this have been studied before, but in the **conformal case**: Law of Iterated Logarithm (Przytycki, Urbanski & Zdunik, Bhourri & Heurteaux)

Here we will work with **non-conformal** maps: $\begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix}$

Mc Mullen, Gatzouras & Peres, Luzia, Barral & Feng, ...

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Dimensions of a measure

Hausdorff dimension of a set A denoted by $\dim_H A$

Definition

Hausdorff dimension of a measure μ (Borel probability measure)

$$\dim_H \mu = \inf \{ \dim_H A : \mu(A) = 1 \}.$$

Definition

Pointwise dimension of a measure μ

$$\underline{d}_\mu(x) = \liminf_{\varepsilon \rightarrow 0} \frac{\log \mu(B(x, \varepsilon))}{\log \varepsilon}, \quad \bar{d}_\mu(x) = \limsup_{\varepsilon \rightarrow 0} \frac{\log \mu(B(x, \varepsilon))}{\log \varepsilon}$$

Proposition

For any Radon measure μ we have $\dim_H \mu = \text{esssup } \underline{d}_\mu$.

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Theorem (Ledrappier-Young 85)

Let f be a C^2 diffeomorphism of a Riemannian manifold M and μ be an invariant measure. Then the **stable and unstable pointwise dimensions** $d_\mu^u(x)$ and $d_\mu^s(x)$ exists for μ -a.e. $x \in M$.

Theorem (Barreira-Pesin-Schmeling 99)

Assume additionally that the **measure is hyperbolic** (no zero Lyapunov exponents). Then the **pointwise dimension** $d_\mu(x)$ exists for μ -a.e. x and $d_\mu(x) = d_\mu^u(x) + d_\mu^s(x)$.

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Let $T: \mathbb{T}^d \circlearrowleft$ be a $C^{1+\alpha}$ *expanding map* and μ_φ be an *equilibrium state* of a Hölder potential φ . Suppose that T has *skew product structure*

$$T(x_1, \dots, x_d) = (f_1(x_1), f_2(x_1, x_2), \dots, f_d(x_1, \dots, x_d)).$$

and that the sequence of *Lyapunov exponents*

$$\lambda_{\mu, i} := \int \log \left| \frac{\partial f_i}{\partial x_i} \right| \circ \pi_i d\mu_\varphi, \quad i = 1, \dots, d$$

is *increasing*. Then there exists $\sigma \geq 0$ such that

$$\frac{\log \mu_\varphi(B(x, \varepsilon)) - \dim_H \mu_\varphi \log \varepsilon}{\sqrt{-\log \varepsilon}}$$

converges as $\varepsilon \rightarrow 0$, in distribution, to a random variable $\mathcal{N}(0, \sigma^2)$.

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Functional CLT and byproducts

Corollary (Median)

If μ_φ is not absolutely continuous then

$$\mu_\varphi(x: \mu_\varphi(B(x, \varepsilon)) \leq \varepsilon^{\dim_H \mu_\varphi}) \rightarrow 1/2.$$

Theorem (Functional CLT or WIP)

The all process converges in distribution in the Skorohod topology:

$$N_\varepsilon(t) := \frac{\log \mu_\varphi(B(x, \varepsilon^t)) - t \dim_H \mu_\varphi \log \varepsilon}{\sqrt{-\log \varepsilon}} \rightarrow \sigma W(t)$$

where W is the standard *Brownian process*.

Several corollaries follow (applying continuous functions of Brownian motion paths): Arc-sine law, Maximum, minimum, etc.

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Finer structure of the invariant measure

Following Przytycki, Urbanski & Zdunik we get (using functional CLT rather than Law of iterated logarithm)

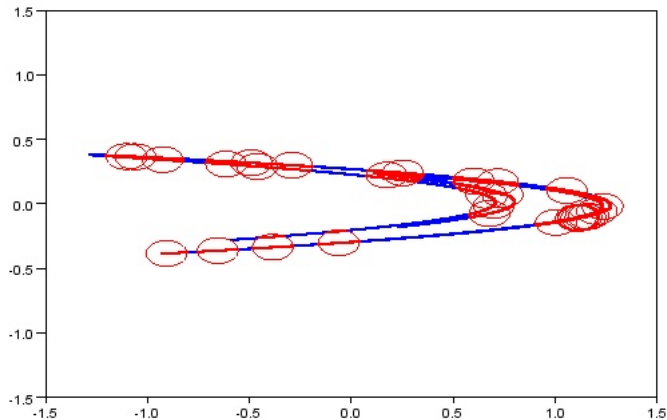
Corollary

Under the assumptions of the main theorem :

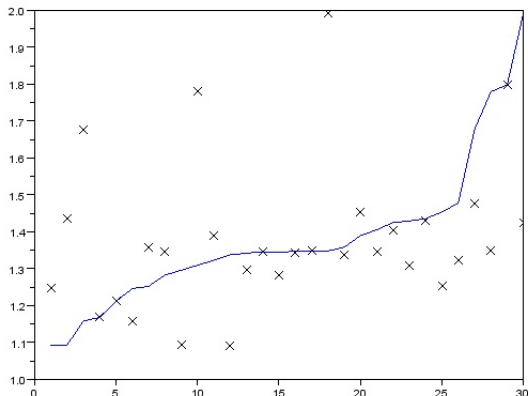
- *the measure μ_φ*
- *the Hausdorff measure in dimension $\dim_H \mu_\varphi$*

*are **mutually singular** iff μ_φ is **not** absolutely continuous wrt **Lebesgue**.*

Numerical (non-rigorous) illustration for Hénon map I

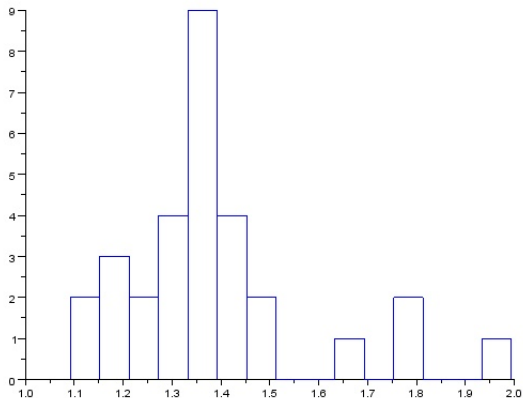


Numerical (non-rigorous) illustration for Hénon map II



$\log(\mu_\varphi(B(x_i, \varepsilon))) / \log(\varepsilon)$ for (30) randomly chosen centers x_i

Numerical (non-rigorous) illustration for Hénon map III



Histogram of $\log(\mu_\varphi(B(x, \varepsilon)))/\log(\varepsilon)$ (for $\varepsilon = 0.1$)

Notations and steps of the proof

We will do the proof in dimension $d = 2$. The map is denoted

$$T(x, y) = (f(x), g(x, y)), \quad (x, y) \in \mathbb{T}^2.$$

Projection $\pi(x, y) = x$. Lyapunov exponents

$$\lambda_{\mu_\varphi}^u = \int \log |f'| \circ \pi d\mu_\varphi < \lambda_{\mu_\varphi}^{uu} = \int \log \left| \frac{\partial g}{\partial y} \right| d\mu_\varphi.$$

Denote the dimension by $\delta := \dim_H \mu_\varphi$. Set Pressure $P(\varphi) = 0$.

Steps of the proof:

- Replace $N_\varepsilon(t)$ by $N'_\varepsilon(t)$ defined symbolically: balls \rightarrow cylinders
- Replace $N'_\varepsilon(t)$ by a non-homogeneous Birkhoff sum $N''_\varepsilon(t)$
- Abstract probabilistic arguments

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A fibered partition

Lemma

There is an invariant splitting $E^u \oplus E^{uu}$ defined μ -a.e. with Lyapunov exponents λ^u and λ^{uu} .

Choose x_0 and y_0 such that $S_0 = \{x_0\} \times \mathbb{T} \cup \mathbb{T} \times \{y_0\}$ is small.
Let \mathcal{R}_n be the **partition into connected components of $T^{-n}(\mathbb{T}^2 \setminus S_0)$** .

Let $\mathcal{P}_n = \pi \mathcal{R}_n$.

Let $F_k = \prod_{j=0}^{k-1} f' \circ f^j$ and $G_k = \prod_{j=0}^{k-1} \frac{\partial g}{\partial y} \circ T^k$.

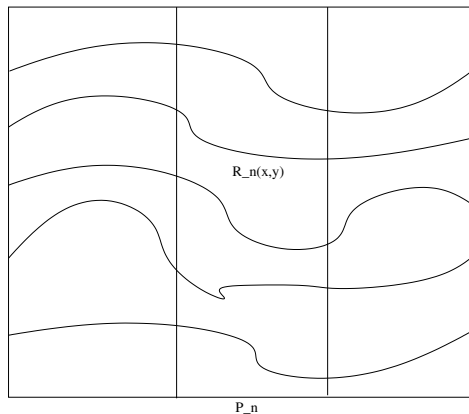
Definition

Let $\varepsilon > 0$. Define

- $n_\varepsilon(x, y)$ the largest integer n s.t. $|G_n(x, y)|\varepsilon \leq 1$
- $m_\varepsilon(x)$ the largest integer m s.t. $|F_m(x)|\varepsilon \leq 1$
- multi-temporal approximation of the ball

$$C_\varepsilon(x, y) = \mathcal{R}_{n_\varepsilon(x, y)}(x, y) \cap \mathcal{P}_{m_\varepsilon(x)}(x) \times \mathbb{T}.$$

The fibered partition \mathcal{R}_n



Approximation of the ball

Lemma

There exists a constant $\underline{c} < 1$, positive a.e., and a function $\bar{c}_\varepsilon > 1$, satisfying $\bar{c}_\varepsilon = O(|\log \varepsilon|)$ a.e. such that

$$C_{\underline{c}\varepsilon}(x, y) \subset B((x, y), \varepsilon) \subset C_{\bar{c}_\varepsilon\varepsilon}.$$

Step 1

If the process $N'_\varepsilon(t) := \frac{\log \mu_\varphi(C_{\varepsilon^t}(x, y)) - t\delta \log \varepsilon}{\sqrt{-\log \varepsilon}}$ converges in distribution to σW then $N_\varepsilon(t)$ also.

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Gibbs measure and projections

The measure μ_φ is $e^{-\varphi}$ -conformal thus $\mu_\varphi(T^{n_\varepsilon} C_\varepsilon) = \int_{C_\varepsilon} e^{-S_{n_\varepsilon} \varphi} d\mu_\varphi$.

Hence $\log \mu_\varphi(C_\varepsilon) \approx S_{n_\varepsilon} \varphi + \log \mu_\varphi(T^{n_\varepsilon} C_\varepsilon)$.

But $T^{n_\varepsilon} C_\varepsilon(x, y) = \pi^{-1} f^{n_\varepsilon} \mathcal{P}_{m_\varepsilon}(x) = \pi^{-1} \mathcal{P}_{m_\varepsilon - n_\varepsilon}(f^{n_\varepsilon}(x))$.

Theorem (Chazottes-Ugalde 09, Kempton-Pollicott, Verbitsky, ...)

The *projection* $\pi_* \mu_\varphi$ is a *Gibbs measure* for f , for a *potential* ψ regular (stretched exponential variations).

Set pressure $P_f(\psi) = 0$. Since $\log \mu_\varphi(T^{n_\varepsilon} C_\varepsilon) \approx S_{m_\varepsilon - n_\varepsilon} \psi \circ f^{n_\varepsilon}$ we obtain

Key lemma

We have $\log \mu_\varphi(C_\varepsilon(x, y)) \approx S_{n_\varepsilon(x, y)}(\varphi - \psi \circ \pi)(x, y) + S_{m_\varepsilon(x, y)} \psi \circ \pi(x, y)$

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Non-homogeneous Birkhoff sum

The **intermediate entropies** $h^u = h_{\pi_*\mu_\varphi}(f)$ and $h^{uu} = h_{\mu_\varphi}(T) - h_{\pi_*\mu_\varphi}(f)$ satisfy $h^u = - \int \psi \circ \pi d\mu_\varphi$, $h^{uu} = - \int (\varphi - \psi \circ \pi) d\mu_\varphi$.

Lemma

Setting $\delta^u = h^u/\lambda^u$ and $\delta^{uu} = h^{uu}/\lambda^{uu}$, the dimension is $\delta = \delta^{uu} + \delta^u$.

Lemma

We have $-\delta \log \varepsilon \approx \delta^{uu} S_{n_\varepsilon} \log \left| \frac{\partial g}{\partial y} \right| + \delta^u S_{m_\varepsilon} \log |f'|$.

Set $\phi_1 = \varphi - \psi \circ \pi + \delta^{uu} \log \left| \frac{\partial g}{\partial y} \right|$ and $\phi_2 = \psi \circ \pi + \delta^u \log |f'|$.

Step 2

If the process $N'_\varepsilon(t) := \frac{S_{n_\varepsilon t} \phi_1 + S_{m_\varepsilon t} \phi_2}{\sqrt{-\log \varepsilon}}$ converges in distribution to σW then $N'_\varepsilon(t)$ also.

Non-homogeneous Birkhoff sum

The **intermediate entropies** $h^u = h_{\pi_*\mu_\varphi}(f)$ and $h^{uu} = h_{\mu_\varphi}(T) - h_{\pi_*\mu_\varphi}(f)$ satisfy $h^u = - \int \psi \circ \pi d\mu_\varphi$, $h^{uu} = - \int (\varphi - \psi \circ \pi) d\mu_\varphi$.

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Setting $\delta^u = h^u/\lambda^u$ and $\delta^{uu} = h^{uu}/\lambda^{uu}$, the dimension is $\delta = \delta^{uu} + \delta^u$.

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If the process $N_\varepsilon''(t) := \frac{S_{n_\varepsilon t} \phi_1 + S_{m_\varepsilon t} \phi_2}{\sqrt{-\log \varepsilon}}$ converges in distribution to σW then $N_\varepsilon'(t)$ also.

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Weak invariance principle

Set $\phi = (\phi_1, \phi_2)$. We have $\int \phi d\mu_\varphi = 0$. Let

$$\mathcal{Y}_k(t) = \frac{1}{\sqrt{k}} S_{[kt]} \phi + \text{Interpolation.}$$

Let Q be the limiting covariance matrix of $\frac{1}{\sqrt{k}} S_k \phi$.

Theorem (WIP, Folklore*)

The process \mathcal{Y}_k converges in distribution towards a bi-dimensional Brownian motion $B(t)$ with covariance Q (in particular $B(t) \sim \mathcal{N}(0, tQ)$).

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Random change of time

Take $a > 1/\lambda^u$.

Set $\mathcal{Z}_k(t_1, t_2) = (\mathcal{Y}_{k,1}(t_1), \mathcal{Y}_{k,2}(t_2))$ for $t_1, t_2 \in [0, a]$.

Set $\Gamma(t) = (t/\lambda^{uu}, t/\lambda^u)$.

Definition

Define the **random change of time** $\Gamma_k(t) = (n_{e^{-kt}}/k, m_{e^{-kt}}/k)$ if both arguments are less than a , $\Gamma_k(t) = \Gamma(t)$ otherwise.

Let $\beta: C([0, 1], \mathbb{R}^2) \rightarrow C([0, 1], \mathbb{R})$ defined by $\beta(u) = u_1 + u_2$

Step 3

- $N''_{e^{-k}}(t) \approx \beta(\mathcal{Z}_k \circ \Gamma_k)(t)$
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Generalizations

The method can be applied to

- conformal expanding maps
- surface diffeomorphisms
- some non uniformly expanding maps

Some questions are left

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Application: log-normal fluctuations of return time

Let $\tau_\varepsilon(x) = \min\{k \geq 1: d(T^k(x), x) < \varepsilon\}$ be the first ε -return time.

Corollary (log-normal fluctuations of first return time ($\sigma \neq 0$))

$$\frac{\log \tau_\varepsilon(x) + \dim_H \mu_\varphi \log \varepsilon}{\sqrt{-\log \varepsilon}} \rightarrow \mathcal{N}(0, \sigma^2).$$

Log-normal fluctuations for **repetition time of first n -symbols** known:
Collet, Galves and Schmitt : exponential law for hitting time + CLT for information function (Gibbsian source).

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Proof.

(1) If (T, μ) mixes rapidly Lipschitz observables and d_μ exists then $\tau_\varepsilon(x) \approx \varepsilon^{-\dim_H \mu}$ μ -a.e. [Rousseau-S 10]. Refine so that log-normal fluctuations are preserved: strong approximation.

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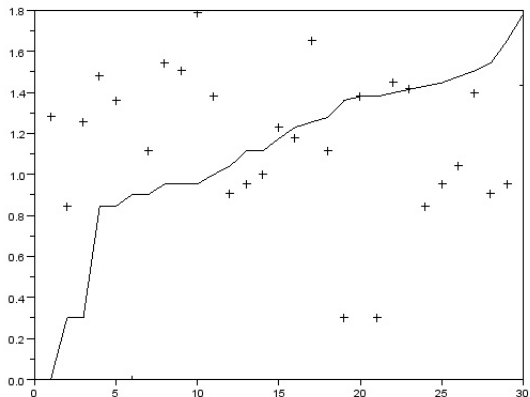
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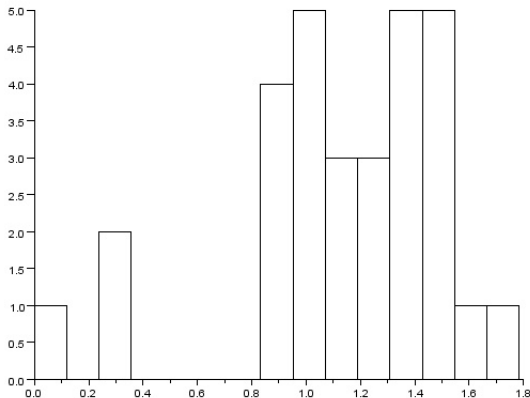
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Numerical (non-rigorous) illustration for Hénon map IV



$\log(\tau_\varepsilon(x_i))/\log(\varepsilon)$ for (30) randomly chosen centers x_i

Numerical (non-rigorous) illustration for Hénon map V



Histogram of $\log(\tau_\varepsilon(x_i))/\log(\varepsilon)$ (for $\varepsilon = 0.1$)