## Rigorous approximation of invariant measures for IFS Joint work with S. Galatolo e I. Nisoli

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- Invariant (stationary) measures.
- Iterate function systems.
- The problem of the computation of stationary measures.
- Tools (spectral approximation).
- Approximation strategy.
- Application to the IFS case.
- A priori contraction estimates.
- Notes on the implementation.
- Related result (on mixing time).

## Invariant measure as a statistical invariant (1/2)

- Let T : X → X be a transformation (dynamical system), where X is a space equipped with a Borel σ-algebra and a Lebesgue measure L.
- A probability measure  $\mu$  is said *invariant measure* if we have

$$\mu(A) = \mu(T^{-1}(A)).$$

• That is, it is invariant applying the *transfer operator*  $L_T$  associated to T acting on the space of measures.  $L_T(\mu)$  is defined as

$$L_{\mathcal{T}}(\mu)(A) = \mu(\mathcal{T}^{-1}(A)), \text{ for each } A \in \mathcal{B}.$$

In this case we have

Theorem 1 (Birkhoff's ergodic)

For each  $\mu$ -integrable function  $f: X \to \mathbb{R}$ 

$$\lim_{n\to\infty}\frac{1}{n}\sum_{i=0}^{n-1}f(T^ix)=\int f\mathrm{d}\mu,\ \mu-\text{almost every }x\in X.$$

## Invariant measure as a statistical invariant (2/2)

$$\lim_{n\to\infty}\frac{1}{n}\sum_{i=0}^{n-1}f(T^ix)=\int f\mathrm{d}\mu,\ \mu-\text{almost every }x\in X.$$

- An invariant measure  $\mu$  determines the statistics of an observable for  $\mu$ -almost all points.
- In general a dynamical system admits several invariant measures, and many of them are supported on a set with Lebesge measure zero.
- An invariant measure  $\mu$  is considered a satisfactory statistical invariant when it describes the statistics of the observables for a Lebsgue-non trival set of points.
- In such a case μ is said *physical measure*. Its support may still have Lebsegue measure zero (e.g. in the case of an attracting fixed point).

## Iterated Function Systems - IFS

- An *Iterated Function System* (IFS) on X is the data of a family of functions  $T_1, \ldots, T_n : X \to X$ , and probabilities  $p_1, \ldots, p_n$  (summing to 1). We have a stochastical dynamical system where at each step a function f is chosen and applied, where each  $f_i$  is chosen with independent probability  $p_i$ .
- The equivalent of the transfer operator for an IFS is defined as

$$L=\sum_i p_i L_{T_i},$$

where  $L_{T_i}$  is the transfer operator corresponding to the transformation  $T_i$ .

- We have the following interpretation: if  $\mu$  is a measure describing the probability distribution of the point x in the space X,  $L(\mu)$  describes the probability distribution of the image under one application of the IFS.
- A measure invariant under L is said stationary measure for the IFS.

## The problem of the rigorous approximation

- The purpouse of this project is developing programs to work concretely with different examples of dynamical systems, and allowing to compute the stationary measure up to a rigorous and certified error.
- The stationary measure is an invariant that it is worth approximating with certified error, as it allows to understand the behaviour of the observables, and approximate other invariants such as the entropy, Lyapunov exponents, and so on.
- We will also study the *speed of convergence to the equilibrium*, for its interest in the estimation of the "escape rates", and the variation under small perturbations ("linear response").
- The long term goal is developing instruments that may be useful in computer assisted proofs.

## Computation of invariant measures

- There exist computable systems having non-computable invariant measure [Galatolo-Hoyrup-Rojas, 2011].
- The "naive" simulation appears to be very effective for approximating invariant measures but fails dramatically for the map of the interval x → 2x. This phenomenon is related to the representation of numbers in base 2 on the computer, and does not appear for the map x → 3x.
- Out approach uses the transfer operator *L*, approximated by a Markov chain  $L_{\delta}$  on a finite number of states. We compute the stationary probability distribution, and relate such distribution to the stationary measure of the system.
- There exist powerful spectral stability results that allow to do this in a suitable functional context (Keller-Liverani's stability theorem), but they are hard to use in practice.

Let  $\mathcal{B}$  be Banach space of signed measure, which we assume to be preserved by L. Assume  $L_{\delta}$  to be an approximation of L.

#### Lemma 2 (Variation on Galatolo-Nisoli '11)

Let  $\mu$ ,  $\mu_{\delta} \in \mathcal{B}$  be probability measures invariant under L,  $L_{\delta}$  respectively. Let  $V = \{\mu \in \mathcal{B} \text{ s.t. } \mu(X) = 0\}$ , and assume  $L_{\delta}(V) \subseteq V$ . Let's assume:

(A) 
$$||L_{\delta}\mu - L\mu||_{\mathcal{B}} \le \epsilon$$
 (true when  $L_{\delta}$  approximates L),  
(B)  $\exists N \text{ such that } ||L_{\delta}^{N}|_{V}||_{\mathcal{B}} < \frac{1}{2}$ ,  
(C) Let  $C = ||\sum_{i \in [0, N-1]} L_{\delta}^{i}|_{V}||_{\mathcal{B}}$ , then  
 $||\mu_{\delta} - \mu||_{\mathcal{B}} \le 2\epsilon C$ .

Other than condition (A), all other conditions only depend on  $L_{\delta}$ , that we assume to be representable on a computer (up to a computable error).

# Approximation in the case of expanding maps of the interval

- A transformation of the interval T is said *piecewise expanding* if the interval can be partitioned in a finite number of interval  $(c_i, c_{i+1})$  such that T is  $C^2$ ,  $|T'| \ge 2$ , and  $T''/(T')^2$  is bounded.
- In the case of piecewise expanding maps we can apply the above strategy using *Ulam approximation* in the space of finite signed measures:

$$L_{\delta} = \pi_{\delta} L \pi_{\delta},$$

where  $\pi_{\delta}(\mu) = E(\mu|\Pi)$ , for a partition of the interval  $\Pi$  in intervals of size  $\delta$ .

- The operator  $\pi_{\delta}$  is a contration in the  $L^1$ -norm (assuming the  $L^1$ -norm of a finite signed measure to be the "total mass").
- Observe that  $\|Id \pi_{\delta}\|_{BV \to L^1} \leq \delta$ .

## Laota-Yorke inequality, and norm estimation

• A piecewise expanding maps satisfies the following theorem:

Theorem 3 (version in Liverani, 2004)

Let T be piecewise expanding, and  $\mu$  be a finite measure on the interval [0,1]. Then

$$\|L_T\mu\|_{BV} \leq \lambda \cdot \|\mu\|_{BV} + B \cdot \|\mu\|_1,$$

$$\lambda = 2 \cdot \left\| \frac{1}{T'} \right\|_{\infty}, \qquad B = \frac{2}{\min(c_i + c_{i+1})} + 2 \left\| \frac{T''}{(T')^2} \right\|_{\infty}$$

• Iterating, if  $\mu$  is as invariant measure, as  $L_T \mu = \mu$  we obtain that

$$\|\mu\|_{BV} \le \frac{B}{1-\lambda}.$$

## Application of the theorem

• Consequently we can satisfy the point (A) of the approximation theorem with respect to the  $L_1$  norm, because

 $\|(L_{\delta}-L)\mu\|_{L^1} \leq \|\mu\|_{BV} \cdot \|L_{\delta}-L\|_{BV \to L^1}$ 

- At point (*B*), the estimation of  $\|L_{\delta}^{N}|_{V}\|_{L^{1}} < \frac{1}{2}$  can be proved by the computer (and is what often requires most computing power!)
- At point (C), the term  $\|\sum_{i \in [0, N-1]} L^i_{\delta}|_V\|_{L^1}$  can be estimated a *priori*, and possibly improved computationally.
- The theorem provides the error between the fixed point of L and the fixed point of  $L_{\delta}$ .
- The fixed point of  $L_{\delta}$  (that is representable as stochastic matrix) can be computed with certified error.
- The goodness of the approximation depends on B! The same L<sub>δ</sub> could be the approximation for different systems, that satisfy Lasota-Yorke inequalities with very different B's.

# Expanding IFS - Example of a rigorous computation (1/2)

• For different values of  $p_1$  and  $p_2 = 1 - p_1$ , let's consider the transformations

$$T_2(x) = 4x + 0.01 \cdot sin(16\pi x), \qquad T_2(x) = 5x + 0.03 \cdot sin(5\pi x).$$

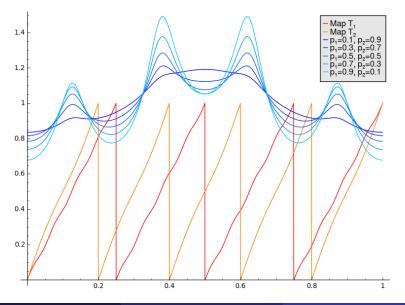
• The values of  $\lambda$ , B and  $\mu_{BV}$  can be computed as

$p_1$		0.3	0.5	0.7	0.9
$\lambda$	0.255202	0.272696	0.290190	0.307683	0.325177
В	2.74553	4.63969	6.53386	8.42802	10.32219
$\ \mu\ _{BV}$	3.68628	6.37931	9.20508	12.17366	15.29615

• The contraction rate and the errors in the L<sup>1</sup> norm are

$ ho_1$	0.1	0.3	0.5	0.7	0.9
N (contraction rate)	8	7	7	8	9
$L^1$ error	0.00180	0.00272	0.00393	0.00594	0.00840
N (a priori c. rate)	34	222	2135	314	37
<i>a priori L</i> <sup>1</sup> error	0.00766	0.0865	1.200	0.233	0.0345

# Expanding IFS - Example of a rigorous computation (2/2)



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### a priori estimation of the contraction rate

In the systems considered obtained from the two maps  $T_0$ ,  $T_1$  and with corresponding operators  $L_0$ ,  $L_1$ , working with a given norm  $\|\cdot\|$ , we have that:

• Any sequence of applications  $L^{\omega} = L_{\omega_1}L_{\omega_2}...L_{\omega_k}$  has uniformly bounded norm  $||L^{\omega}|| \leq C$ , for each sequence  $\omega \in \{0,1\}^k$  of any length k k.

•  $L_0$ ,  $L_1$  are contractions, and we can assume that  $\|L_0^{n_0}\| \leq \frac{1}{2C}$  and  $\|L_1^{n_1}\| \leq \frac{1}{2C}$ .

Theorem 4 (Galatolo, M., Nisoli)

For each  $p \in [0,1]$ , and putting  $N = \max\{n_0, n_1\}$ , then

$$\left\| (pL_0 + (1-p)L_1)^M \right\| < \frac{1}{2}, \quad M \ge N - 1 + N \frac{\log 2C}{-\log \left(1 - \frac{p^{n_0}}{2} - \frac{(1-p)^{n_1}}{2}\right)}.$$

## Sketch of proof

- The contraction rate of  $L^n$  can be estimated expanding  $L = pL_0 + (1-p)L_1$ , and considering all the weighted terms  $L^{\omega} = L_{\omega_1}L_{\omega_2}\dots L_{\omega_k}$  appearing in the expansion, for a certain n.
- Increasing the length *n*, we can estimate the contraction rate with a linear recurrence depending on the contraction rates of the previous *n*.
- The linear recurrence has order  $N = \min\{n_0, n_1\}$ , and the characteristic polynomial is of the form

$$X^N - p_{N-1}X^{N-1} - \cdots - p_1X - p_0.$$

- The p<sub>i</sub> are positive and have sum slightly smaller than 1, so we can prove that the biggest real root α has absolute value < 1.</li>
- We obtain that  $L^n$  has contraction rate  $\leq K\alpha^n$  for some K, and estimating K and  $\alpha$  we can predict when  $||L^n|| \leq 1/2$ .

## Contracting IFS - Kantorovich-Wasserstein distance

- In the case of a IFS formed by contracting maps, we can apply the same strategy, but the functional spaces need to be completely different, because for a contraction T in  $\mathbb{R}^n$  the corresponding  $L_T$  is not a contraction in  $L^p$  or BV.
- A space with this property is the dual of Lipschitz, that is the measures for which

$$\|\mu\|_W = \sup_{\phi \in C^0(X): Lip(\phi) \le 1} \int_X \phi d\mu,$$

is finite. Such a distance is also known as *Kantorovich-Wasserstein distance*, or *earth-moving distance*, well known in Transportation Theory.

- $\bullet$  Such a norm is only defined for  $\mu$  having zero average, but this is sufficient for us.
- If T contracts by  $\alpha$  at least, then we have  $||L_T||_W \leq \alpha$ .

## Contracting IFS - Discretization

- We will work assuming that X is a bounded domain in ℝ<sup>n</sup>, equipped with the Manhattan distance (L<sup>1</sup> distance on the coordinates).
- Given a rectangular lattice of  $\delta$ -spaced points  $p_i$ , the projection is given by

$$\pi_{\delta}(\mu) = \sum_{i} \left( \int h_{\mathcal{P}_{i}} \mathrm{d}\mu 
ight) \cdot \delta_{\mathcal{P}_{i}}$$

where  $h_{p_i}$  is a certain hat function centered in  $p_i$ .

Proposition 1 (Galatolo, M., Nisoli)

If  $\|\mu\|_{W} \le 1$ , then  $\|\pi_{\delta}\mu\| \le 1$ .

Proposition 2 (Galatolo, M., Nisoli)

Putting  $L_{\delta} = \pi_{\delta} L \pi_{\delta}$ , we have

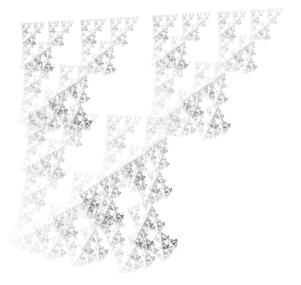
$$\|L-L_{\delta}\|_{L^1\to W} \leq (\alpha+1)\frac{n\delta}{2}.$$

## Contracting IFS - Example of a rigorous computation (1/2)

- Computationally this case is easier, because the contraction rate is already know, and as a consequence of the approximation theorem we have  $\|\mu \mu_{\delta}\|_{W} \leq \frac{(1+\alpha)n\delta}{2(1-\alpha)}$ .
- Let's consider the transformations  $T_1, \ldots, T_4$  of the square  $X = [0,1] \times [0,1]$  defined as
  - T1: scaling by 0.4 around (0.6, 0.2) with rotation of  $\pi/6$ ,
  - T2: scaling by 0.6 around (0.05, 0.2) with rotation of  $-\pi/30$ ,
  - T3: scaling by 0.5 around (0.95, 0.95),
  - T4: scaling by 0.45 around (0.1, 0.9).
- Let's take probabilities  $p_1 = 0.18$ ,  $p_2 = 0.22$ ,  $p_3 = 0.3$ ,  $p_4 = 0.3$ , and a lattice of  $2^{10} \times 2^{10}$  points, with  $\delta = 2^{-10}$ . The contraction rate  $\alpha$  is  $\leq 0.659430$ , and the error (in the  $\|\cdot\|_W$  norm) can be estimated as

$$\|\mu - \mu_{\delta}\|_{W} \le \frac{(1+lpha)n\delta}{2(1-lpha)} \le 0.0047583.$$

# Contracting IFS - Example of a rigorous computation (2/2)



## Notes on the implementation

- Our framework is written in Python and uses the libraries from the computer algebra system Sage.
- A matrix approximating  $L_{\delta}$  is computed with certified error using interval arithmetics, and interval Newton method for computing the Ulam approximation.
- The computationally intensive part is implemented via a program using OpenCL for computing on the GPU.
- In the contractive case, we can restrict the computation to a subset of the grid containing the attractor (on the line of what was explained by Kathrin Padberg-Gehle yesterday).

## Convergence to the equilibrium

• Assume *L* to satisfy the inequality

$$\|L^n f\|_s \leq A\lambda_1^n \|f\|_s + B\|f\|_w.$$

• Let  $L_{\delta}$  be an approximation satisfying

$$\|(L_{\delta}^n-L^n)f\|_w\leq \delta(C\|f\|_s+nD\|f\|_w).$$

• Assume that L preserves V, and  $\|(L_{\delta}|_V)^{n_1}\| \leq \lambda_2$ .

Theorem 5 (Galatolo, Nisoli, Saussol)

$$\begin{pmatrix} \|L^{in_1}(g)\|_s \\ \|L^{in_1}(g)\|_w \end{pmatrix} \preceq M \cdot \begin{pmatrix} \|g\|_s \\ \|g\|_w \end{pmatrix}, \text{ for } M = \begin{pmatrix} A\lambda_1^{n_1} & B \\ \delta C & \delta n_1 D + \lambda_2 \end{pmatrix},$$

for each  $g \in V$ , and in particular if  $\rho$  is the biggest eigenvalue of M then

$$\|L^{in_1}g\|_s \leq rac{
ho^i}{a}\|g\|_s, \quad \|L^{in_1}g\|_w \leq rac{
ho^i}{b}\|g\|_s \quad ext{ for explicit a, b.}$$