

Lyapunov exponent of a Lennard-Jones gas: cumulant expansion

Raúl O. Vallejos (CBPF)

Celia Anteneodo (Puc-Rio)

Leonardo Cirto (CBPF, MSc)

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Purpose

- Can the cumulant-expansion approach estimate the Lyapunov exponent of a (dilute) Lennard-Jones gas?

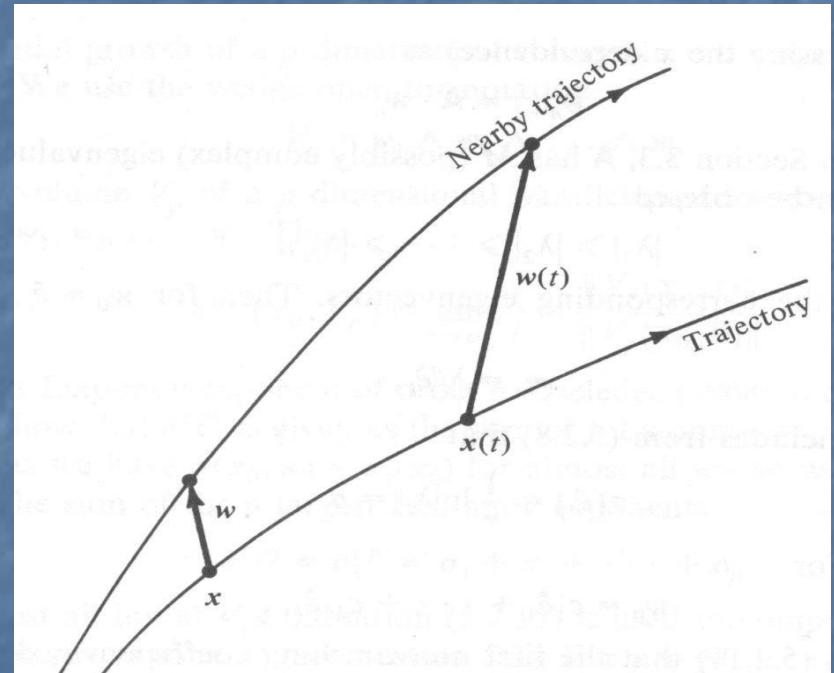
The Lyapunov exponent

Dynamical system

$$\frac{dx}{dt} = f(x), \quad x \in \mathbb{R}^n$$

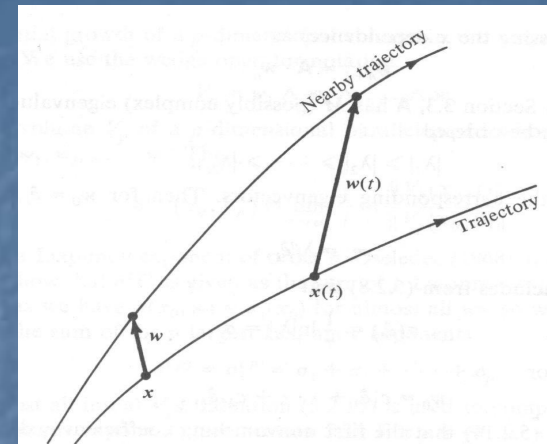
Asymptotically

$$|w(t)| \approx |w| e^{\lambda t}$$



Tangent dynamics

In the limit $|w| \rightarrow 0$, $w \rightarrow \xi$:



$$\frac{d\xi}{dt} = Df_{x(t)} \cdot \xi$$

Linear system of differential equations with time-dependent coefficients

Operational definition of Lyapunov exponent :

$$\lambda = \lim_{t \rightarrow \infty} \frac{1}{t} \ln |\xi(t)|$$

λ does not depend on initial conditions

$$x_0, \xi_0$$

Why λ ?

λ quantifies sensitivity to initial conditions,
instability, unpredictability, chaos

In classical statistical mechanics:

$\lambda > 0$ necessary for validity of microcanonical
formalism

$\lambda \approx 0$ signals thermodynamic anomalies

Theory (Hamiltonian Systems)

$$\frac{d\xi}{dt} = A(t) \xi$$

$$\begin{pmatrix} \underline{0} & \underline{1} \\ -\underline{V}(t) & \underline{0} \end{pmatrix}$$

Hessian

Theory (Hamiltonian Systems)

$$1) \quad \lambda = \lim_{t \rightarrow \infty} \frac{1}{2t} \ln |\xi(t)|^2$$

$$\frac{d\xi}{dt} = A(t) \xi$$

$$\begin{pmatrix} \underline{0} & \underline{1} \\ -\underline{V}(t) & \underline{0} \end{pmatrix}$$

Hessian

Theory (Hamiltonian Systems)

$$1) \quad \lambda = \lim_{t \rightarrow \infty} \frac{1}{2t} \ln |\xi(t)|^2$$

$$2) \quad \lambda = \lim_{t \rightarrow \infty} \frac{1}{2t} \left\langle \ln |\xi(t)|^2 \right\rangle_{x_0, \xi_0}$$

$$\frac{d\xi}{dt} = A(t) \xi$$

$$\begin{pmatrix} \underline{0} & \underline{1} \\ -\underline{V}(t) & \underline{0} \end{pmatrix}$$

Hessian

Theory (Hamiltonian Systems)

$$1) \quad \lambda = \lim_{t \rightarrow \infty} \frac{1}{2t} \ln |\xi(t)|^2$$

$$2) \quad \lambda = \lim_{t \rightarrow \infty} \frac{1}{2t} \left\langle \ln |\xi(t)|^2 \right\rangle_{x_0, \xi_0}$$

$$3) \quad \lambda \approx \lim_{t \rightarrow \infty} \frac{1}{2t} \ln \left\langle |\xi(t)|^2 \right\rangle_{x_0, \xi_0} \equiv \lambda_2$$



if intermittency weak enough

$$\frac{d\xi}{dt} = A(t) \xi$$



$$\begin{pmatrix} \underline{0} & \underline{1} \\ -\underline{V}(t) & \underline{0} \end{pmatrix}$$

Hessian

A theory for λ_2

$$\frac{d\xi}{dt} = A(t)\xi \quad \Leftrightarrow \quad \frac{d\psi}{dt} = -iH(t)\psi$$

Analogous to a Schrödinger equation with a time-dependent nonhermitian Hamiltonian

A theory for λ_2

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Analogous to a Schrödinger equation with a time-dependent nonhermitian Hamiltonian

Solution:

$$\xi(t; x_0, \xi_0) = T e^{\int_0^t A(t_1; x_0) dt_1} \xi_0$$

time ordering

Second moments

$$\lambda_2 = \lim_{t \rightarrow \infty} \frac{1}{2t} \ln \left\langle |\xi(t)|^2 \right\rangle_{x_0, \xi_0}$$

$$\left\langle |\xi|^2 \right\rangle = \text{Tr} \left\langle \xi \xi^T \right\rangle$$

matrix of second moments

$$\frac{d\xi}{dt} = A\xi \Rightarrow \frac{d}{dt} \xi \xi^T = A \xi \xi^T + \xi \xi^T A^T \equiv \hat{A} \xi \xi^T$$

linear operator

$$\left\langle \xi \xi^T(t) \right\rangle_{x_0, \xi_0} = \left\langle T e^{\int_0^t \hat{A}(t_1; x_0) dt_1} \right\rangle_{x_0} \underbrace{\left\langle \xi_0 \xi_0^T \right\rangle_{\xi_0}}_{\propto \mathbf{1}}$$

Preparatory step

$$A = \langle A \rangle + \delta A(t) = \begin{pmatrix} \underline{0} & \underline{1} \\ -\langle \underline{V} \rangle & \underline{0} \end{pmatrix} + \begin{pmatrix} \underline{0} & \underline{0} \\ -\delta \underline{V}(t) & \underline{0} \end{pmatrix}$$



“free Hamiltonian”



perturbation



$$\hat{A} = \langle \hat{A} \rangle + \delta \hat{A}$$

→ Switch to the interaction representation

The cumulant expansion

(Kubo, van Kampen, Fox)

Fluctuations of small amplitude and/or short correlation time

$$\left\langle \mathcal{T} e^{\int_0^t \hat{A}(t_1; x_0) dt_1} \right\rangle = e^{\hat{O}t}$$

\hat{O} is time-independent

$$\hat{O} = \langle \hat{A} \rangle + \int_0^\infty d\tau \left\langle \delta \hat{A}(t) e^{\tau \langle \hat{A} \rangle} \delta \hat{A}(t - \tau) e^{-\tau \langle \hat{A} \rangle} \right\rangle + \dots$$

average + integrated autocorrelation function + ...

The cumulant expansion II

$$\langle |\xi|^2 \rangle = \text{Tr} \langle \xi \xi^T(t) \rangle = \text{Tr} e^{\hat{O}t} \underline{\underline{1}}$$

The generalized Lyapunov exponent is given by

$$\lambda_2 = \frac{1}{2} \max \Re(\text{eigenvalues of } \hat{O})$$

Next: calculate and diagonalize \hat{O} . Use symmetries!

Relevant subspace

In some cases \rightarrow 3D,
ex., dilute gas, Hamiltonian mean field XY model

Other cases \rightarrow restrict to 3D subspace
(mean field approximation in tangent space)

Final result (second order)

$$\|\hat{O}\| = \begin{pmatrix} 0 & 0 & 2 \\ 2\sigma^2\tau_c^{(1)} & -2\sigma^2\tau_c^{(3)} & -2\mu \\ -\mu + 2\sigma^2\tau_c^{(2)} & 1 & -2\sigma^2\tau_c^{(3)} \end{pmatrix}$$

3x3 matrix

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3x3 matrix

$$\mu = \frac{1}{N} \text{Tr} \langle \underline{\underline{\mathbf{V}}} \rangle_{\mu}$$

average

$$\sigma^2 = \frac{1}{N} \text{Tr} \langle (\underline{\underline{\delta\mathbf{V}}})^2 \rangle_{\mu}$$

variance

$$\tau_c^{(k)} = \int_0^{\infty} d\tau \tau^{k-1} f(\tau)$$

correlation times

$$f(\tau) = \frac{1}{N\sigma^2} \text{Tr} \langle \underline{\underline{\delta\mathbf{V}}}(0) \underline{\underline{\delta\mathbf{V}}}(\tau) \rangle_{\mu} = \frac{1}{N\sigma^2} \sum_{i,j=1}^N \langle \delta\mathbf{V}_{ij}(0) \delta\mathbf{V}_{ij}(\tau) \rangle_{\mu}$$

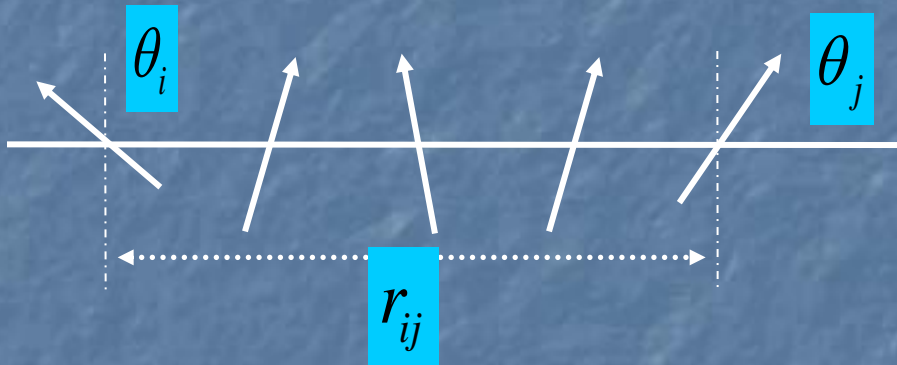
normalized autocorrelation function

Special case

Short correlation time, negligible average fluctuations

$$\lambda_2 \approx \left(\frac{\sigma^2 \tau_c^{(1)}}{2} \right)^{1/3}$$

Testing the theory

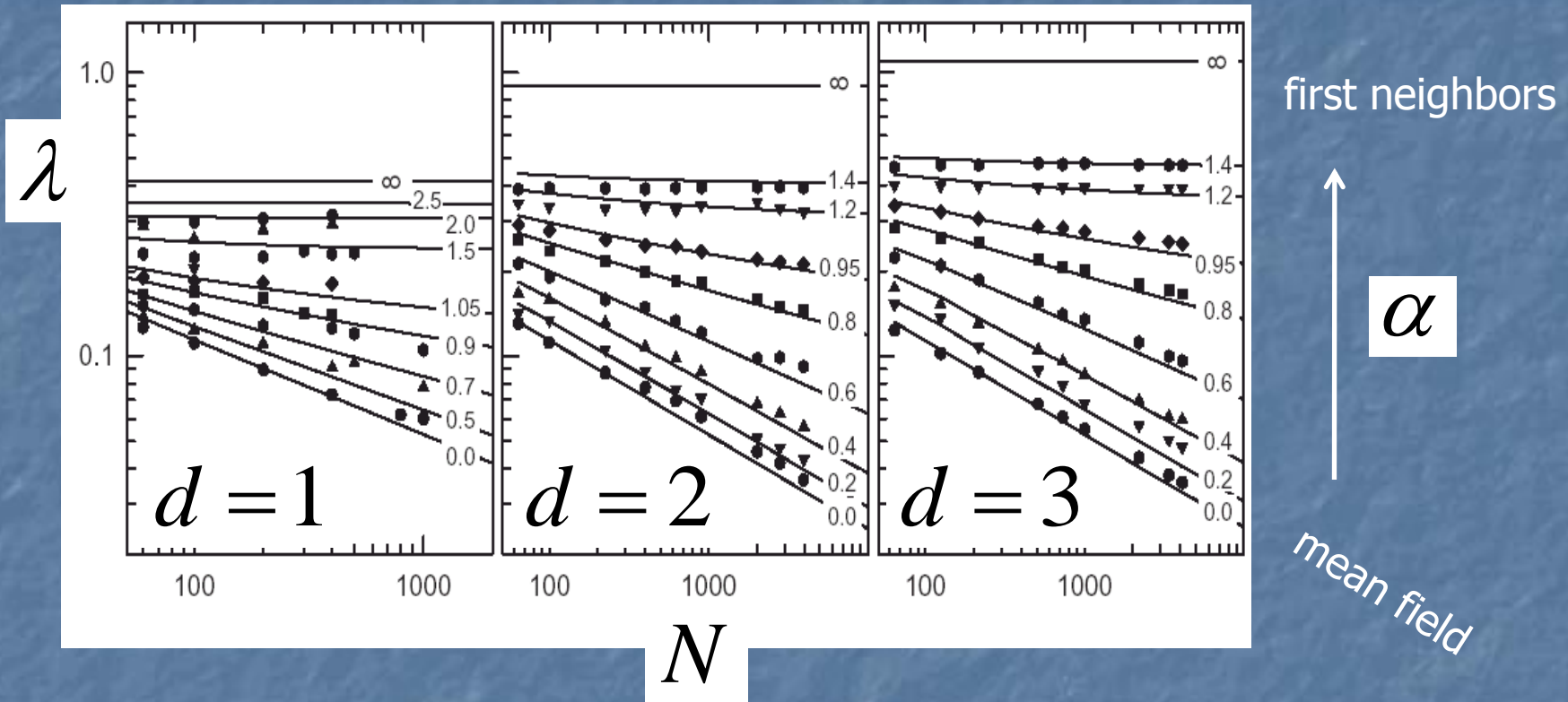


α -XY Hamiltonian model

$$H = \sum_{i=1}^N \frac{L_i^2}{2I} + \frac{J'}{2} \sum_{i,j=1}^N \frac{1 - \cos(\theta_i - \theta_j)}{r_{ij}^\alpha}$$

Results λ_{num} vs λ_{2theo}

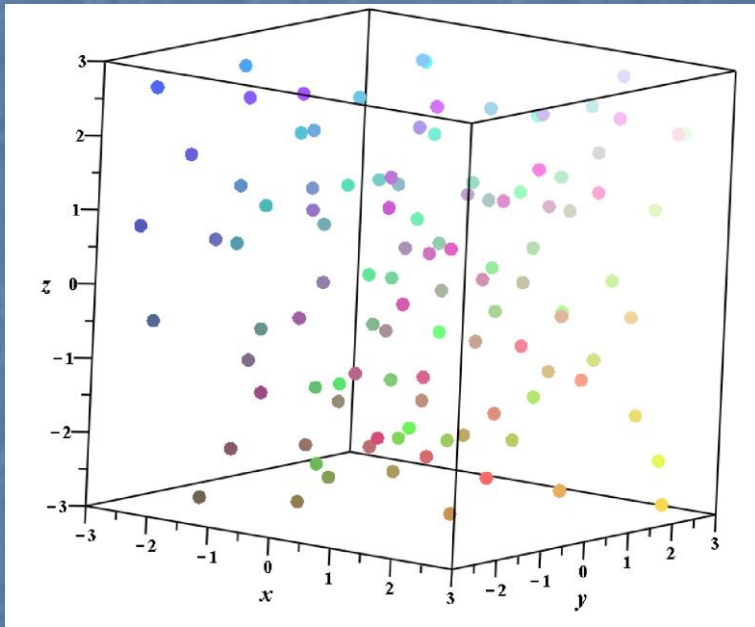
ROV & C. Anteneodo
Physica A (2004)



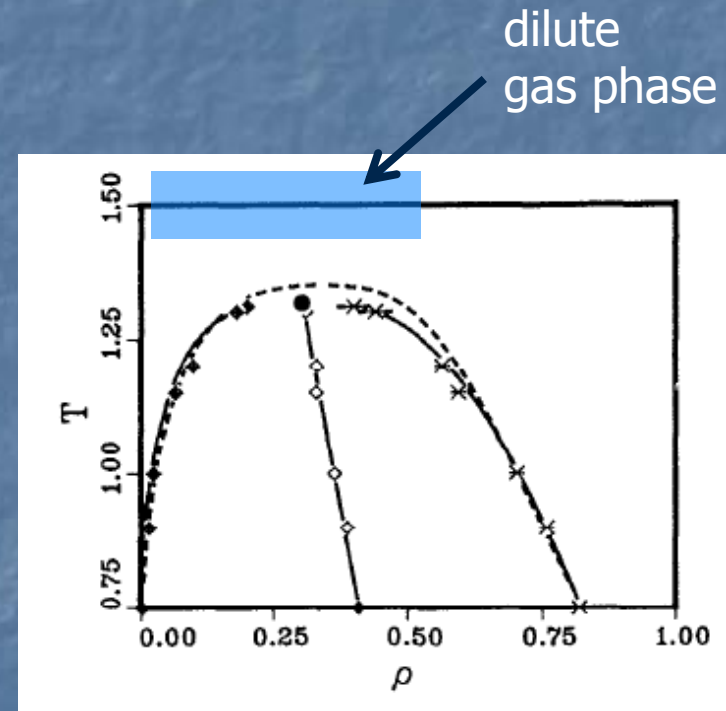
numerics { Latora, Rapisarda, Ruffo, PRL (1998)
 Anteneodo & Tsallis, PRL (1998)
 Campa, Giansanti, Moroni, Tsallis, PLA (2001)

The Lennard-Jones gas

The Lennard-Jones gas

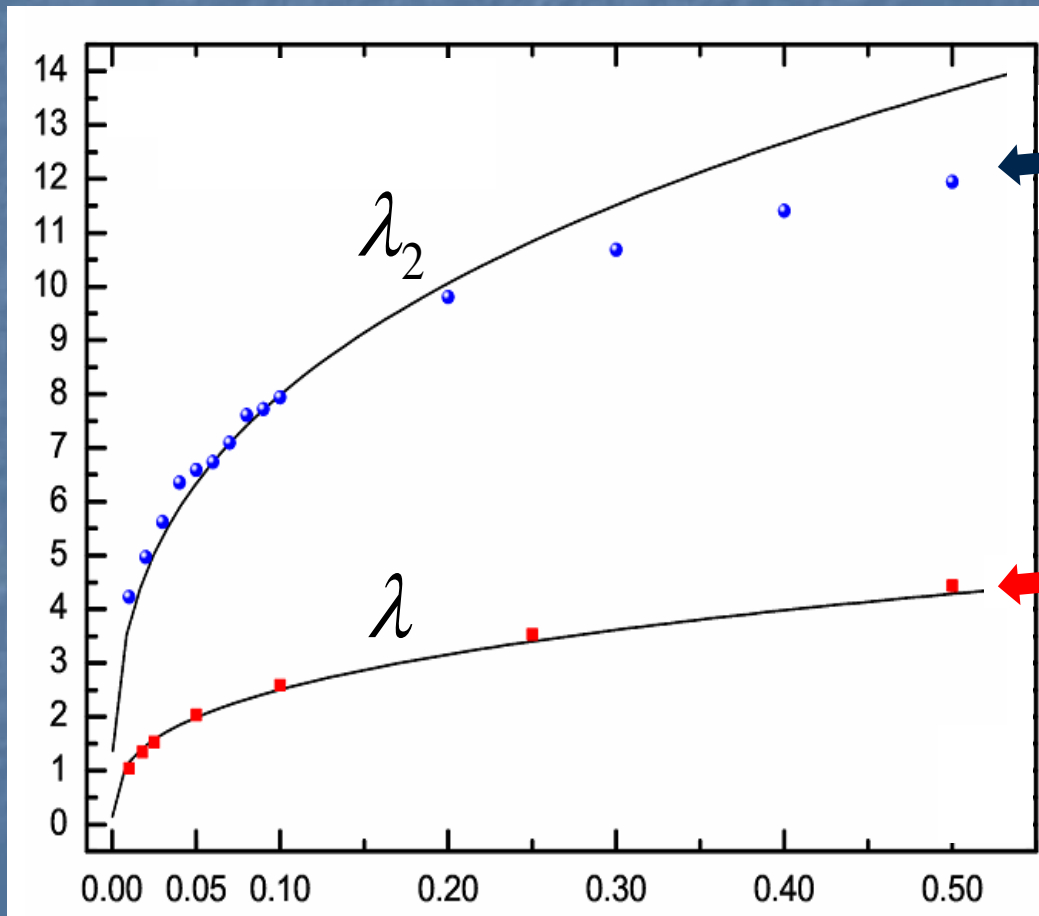


N=108



Smit, *JCP* (1992)

Theory vs numerics



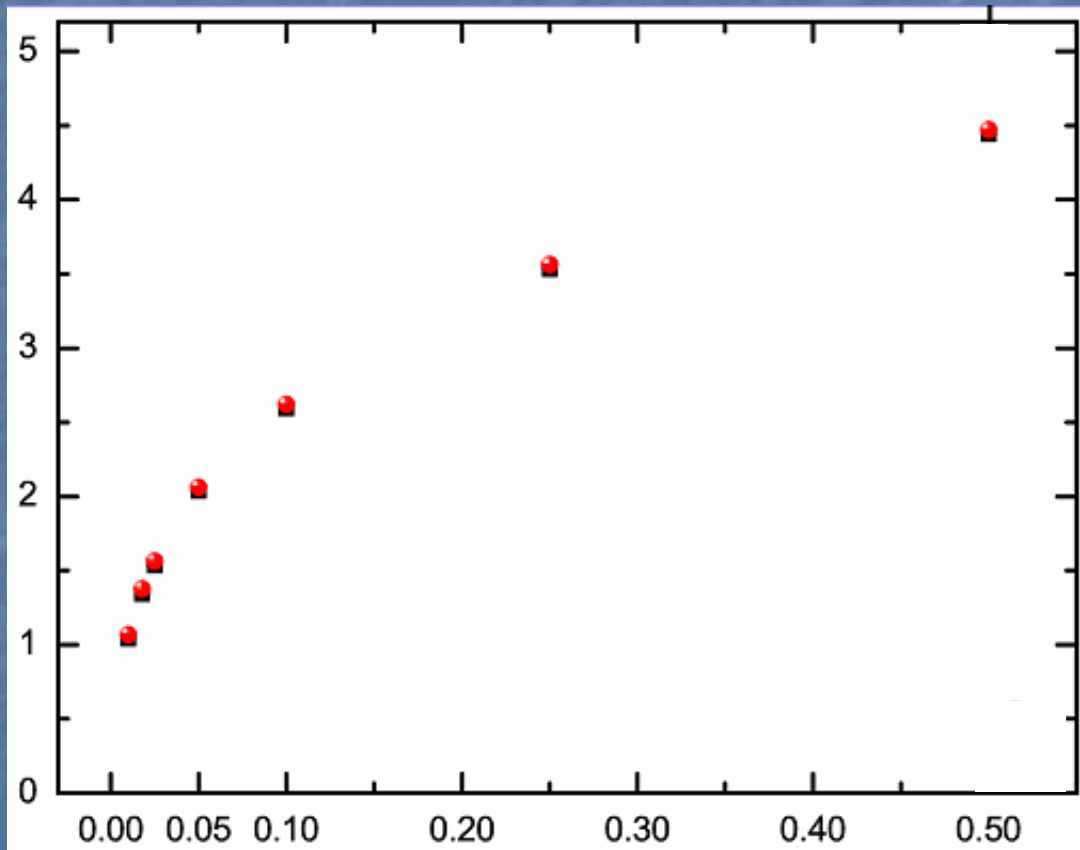
theory

numerical

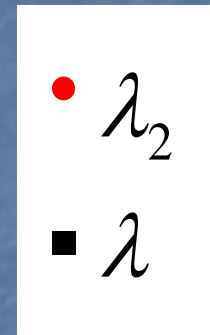
= Romero Bastida,
Braun, JPA08

ρ

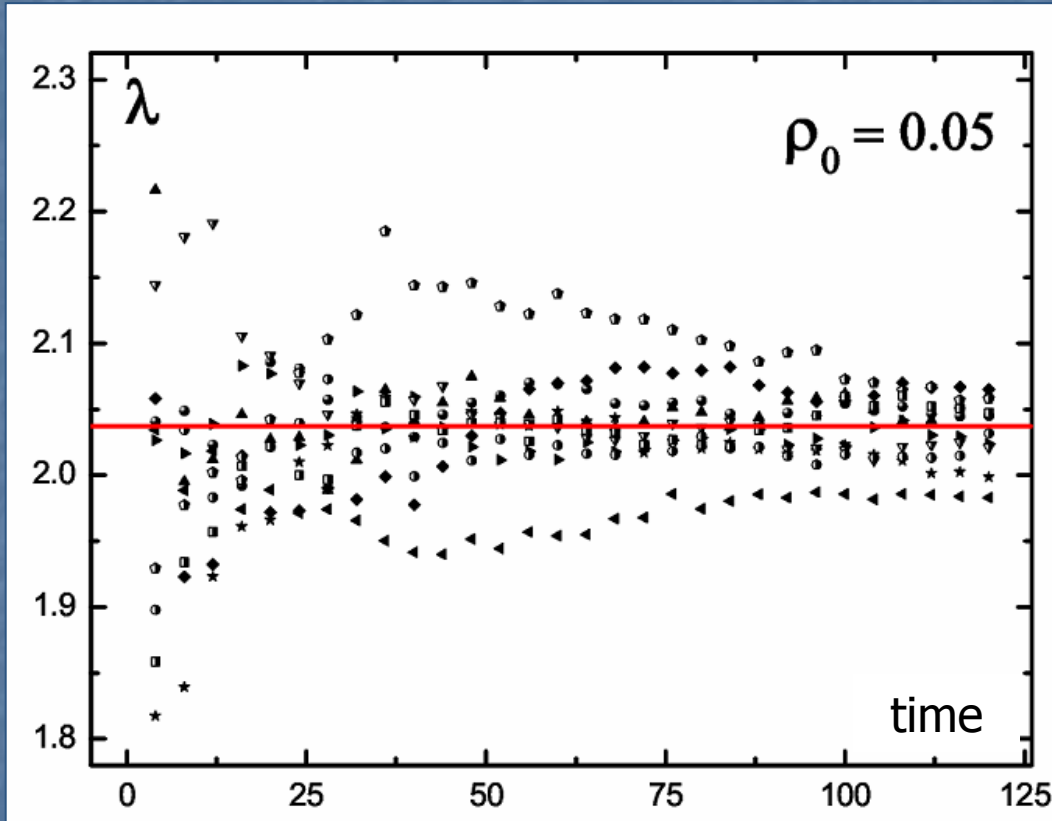
Generalized vs standard LE (numerical)



ρ



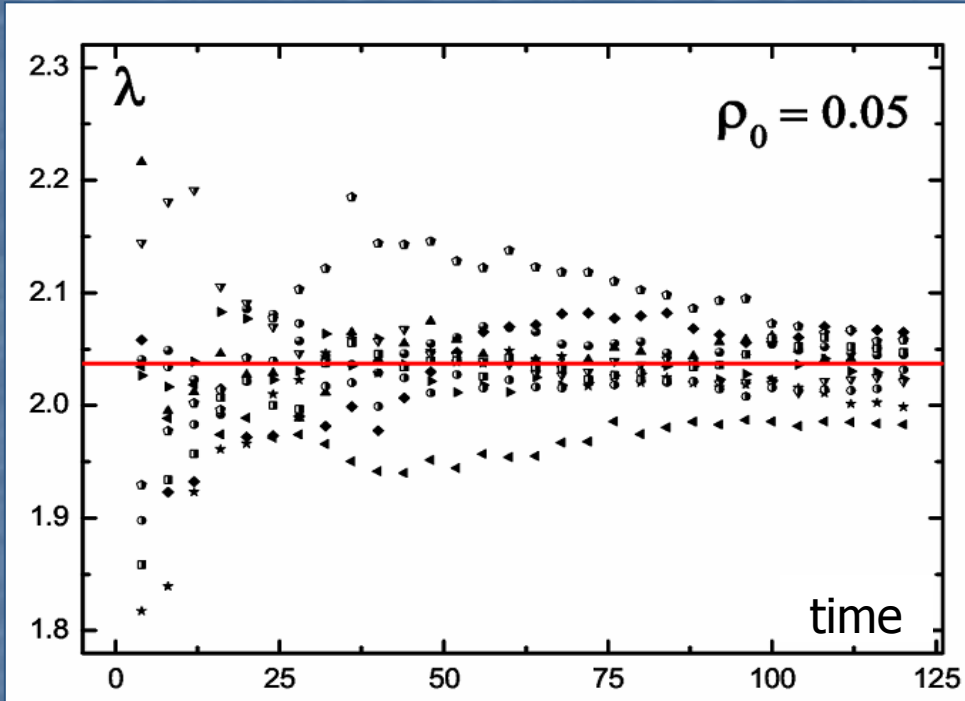
However ...



$$\lambda \approx \left\langle \frac{1}{2t} \ln |\xi|^2 \right\rangle_{x_0, \xi_0}$$

average over
finite-time
Lyapunov exponents

If simple sampling ...

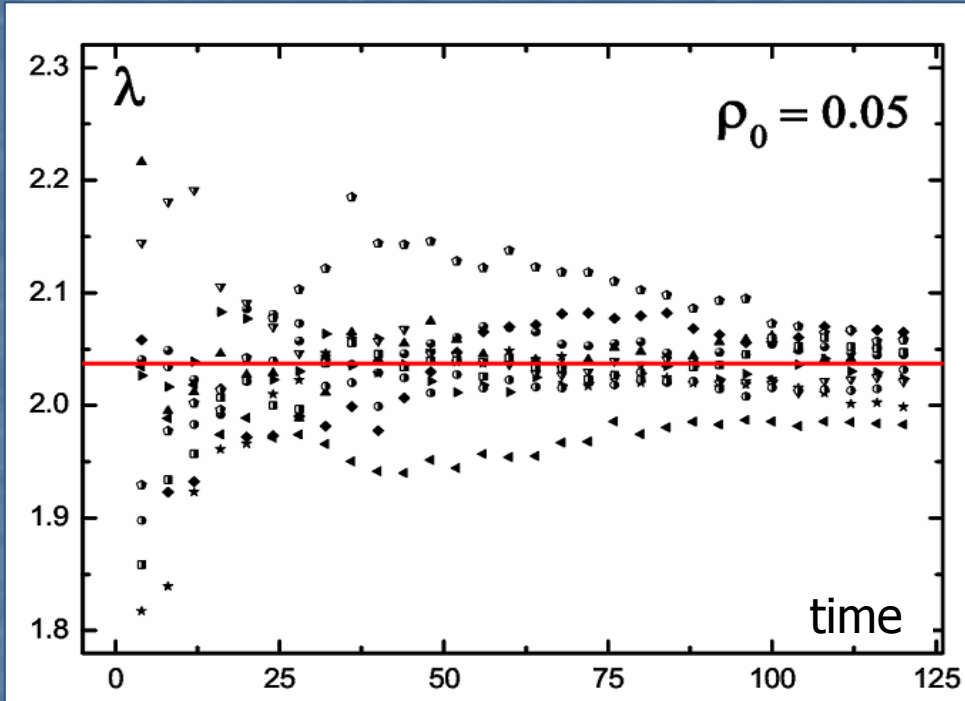


$$\begin{aligned}\lambda_2 &\approx \frac{1}{2t} \ln \langle |\xi|^2 \rangle \\ &= \frac{1}{2t} \ln \langle e^{2t \lambda^{(i)}} \rangle\end{aligned}$$

dominated by tails

Simple sampling is bound to fail

If simple sampling ...

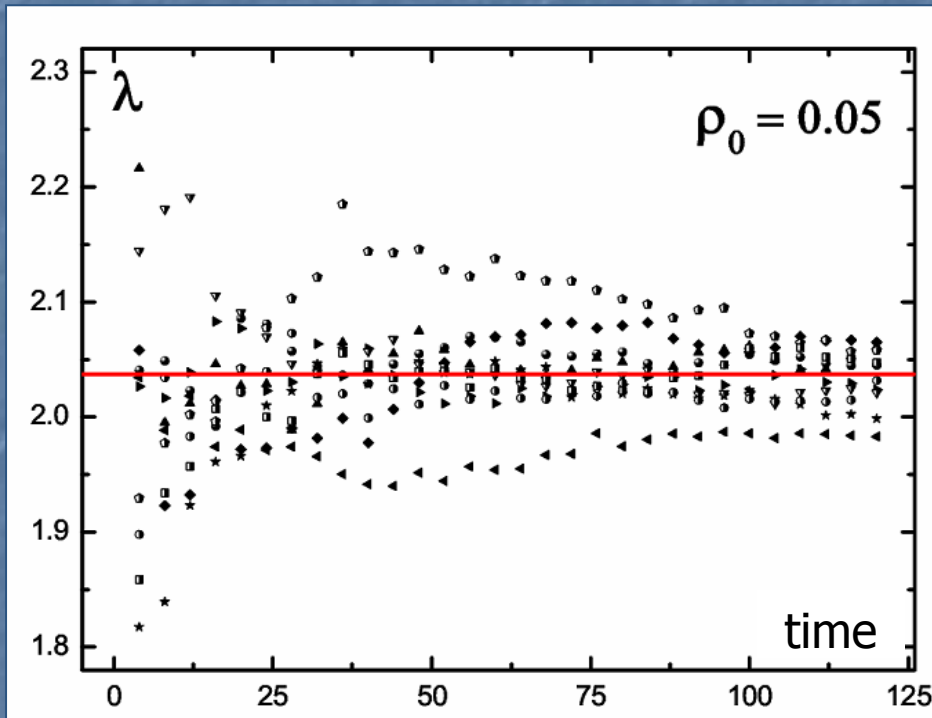


$$\begin{aligned}\lambda_q &\approx \frac{1}{qt} \ln \langle |\xi|^q \rangle \\ &= \frac{1}{qt} \ln \langle e^{qt \lambda^{(i)}} \rangle\end{aligned}$$

dominated by tails

The larger the q , the worse the performance of SS

Simple sampling + Gaussian?



} Gaussian approximation

Some improvement but still unsatisfactory

Importance sampling!

stochastic maps

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Estimating generalized Lyapunov exponents for products of random matrices

J. Vanneste*

of Mathematics and Maxwell Institute for Mathematical Sciences, University of Edinburgh, Edinburgh EH9 3JZ, Uni

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We discuss several techniques for the evaluation of the generalized Lyapunov exponents which characterize the growth of products of random matrices in the large-deviation regime. A Monte Carlo algorithm that performs importance sampling using a simple random resampling step is proposed as a general-purpose numerical method which is both efficient and easy to implement. Alternative techniques complementing this

cloning and pruning

Test: random frequency oscillator

=1D Anderson localization problem

6N equations (ex., N=108)
for 3D LJ

$$\frac{d\xi}{dt} = A(t) \xi$$

$$\begin{pmatrix} \underline{0} & \underline{1} \\ -\underline{\underline{V}}(t) & \underline{0} \end{pmatrix}$$

Hessian

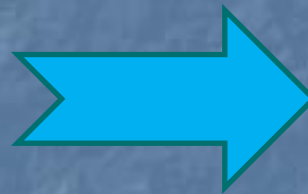
Test: random frequency oscillator

=1D Anderson localization problem

6N equations (ex., N=108)
for 3D LJ

2 equations

$$\frac{d\xi}{dt} = A(t) \xi$$



$$\begin{pmatrix} \dot{\xi}_1 \\ \dot{\xi}_2 \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ -v(t) & 0 \end{pmatrix} \begin{pmatrix} \xi_1 \\ \xi_2 \end{pmatrix}$$

$$\begin{pmatrix} \underline{0} & \underline{1} \\ -\underline{V}(t) & \underline{0} \end{pmatrix}$$

Hessian

Mimic dilute LJ: white Poisson noise

$$\begin{pmatrix} \dot{\xi}_1 \\ \dot{\xi}_2 \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ -\nu(t) & 0 \end{pmatrix} \begin{pmatrix} \xi_1 \\ \xi_2 \end{pmatrix}$$

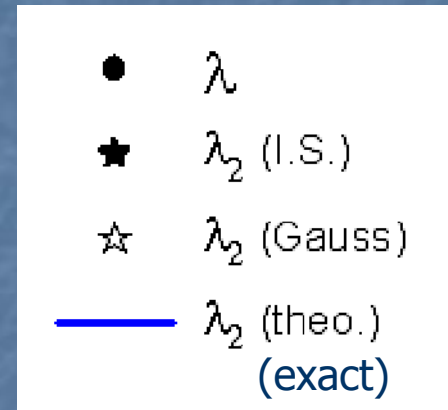
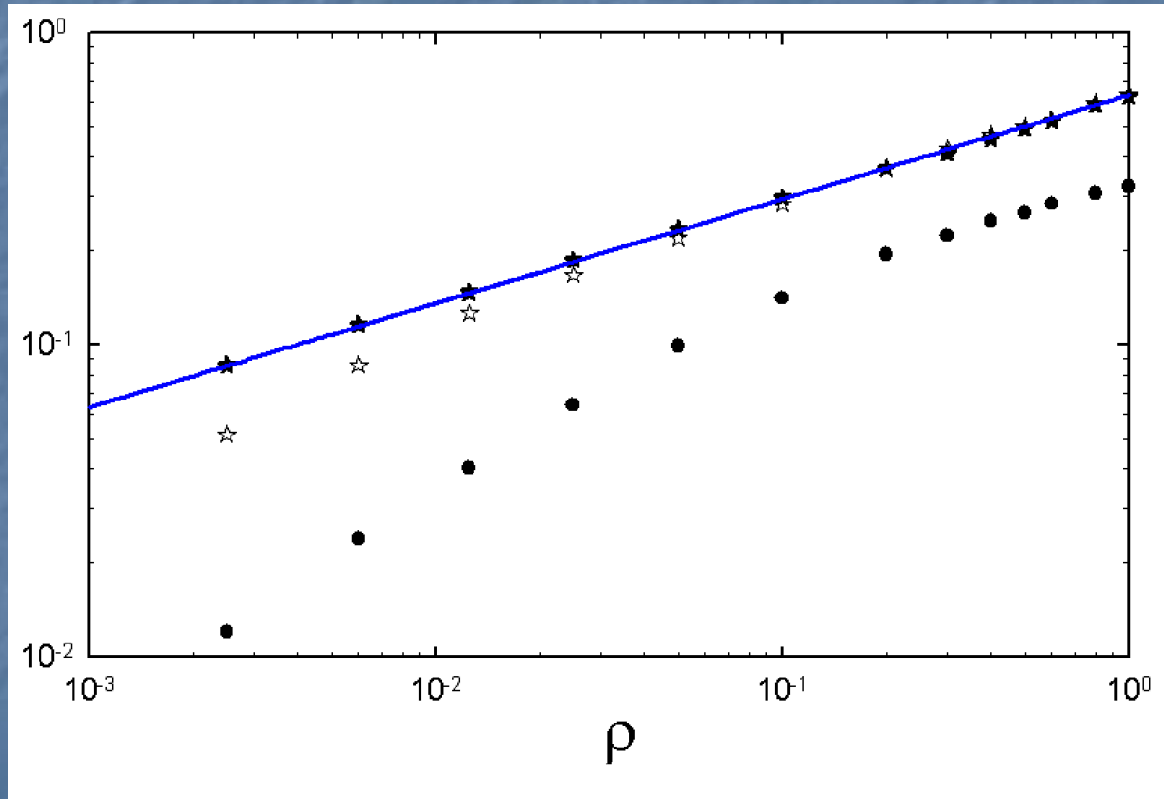


$$\nu(t) = \sum_k A_k \delta(t - \tau_k)$$

ex., i.i. Gaussians

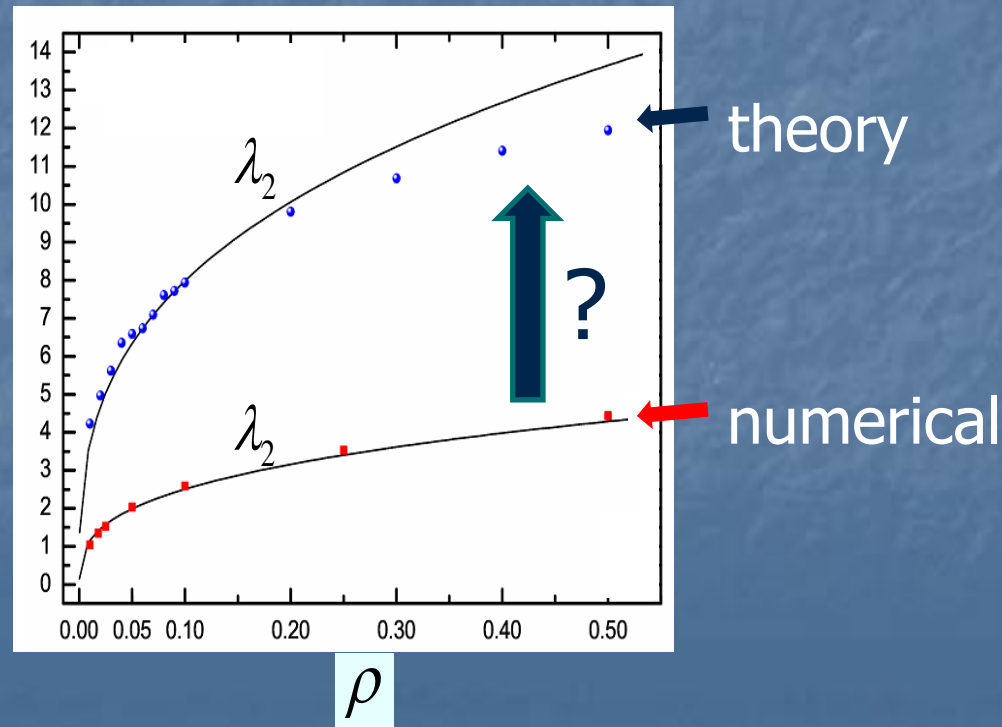
Poisson sequence

Results (preliminary)



Conclusions

- Adapt importance-sampling MC to deterministic LJ dynamics



Thanks!

<http://www.cbpf.br/~vallejos/publications>

The Kubo number

$$\eta_K = \sigma_\lambda (\tau_c^{(1)})^2 \propto \sqrt{\rho_0}$$

