

# Nonlinear Oscillator: An Attempt to Predict Butterfly Effect by Machine learning

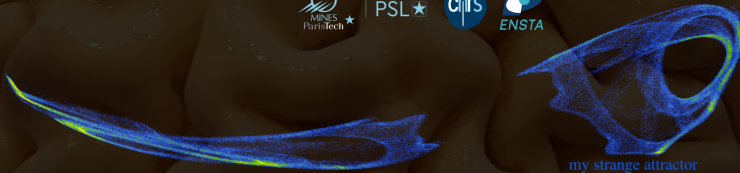
Vladislav A. YASTREBOV<sup>1</sup>, Yirun ZOU<sup>1,2</sup>

<sup>1</sup>MINES ParisTech, PSL University, Centre des Matériaux, CNRS UMR 7633, Evry

<sup>2</sup>ENSTA, Palaiseau



PSL ★



*Big SIMS*  
Evry, France  
September 10, 2019

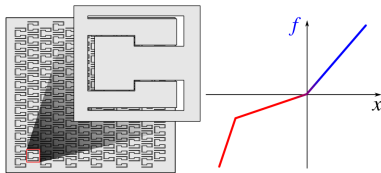


# Outline

- 1 Multimodulus materials: mechanics and dynamics
- 2 Contact-based architecture
- 3 Some results
- 4 Artificial Neural Network
- 5 Time series prediction
- 6 Classification
- 7 Preliminary conclusions



# Introduction





# Asymmetry in materials

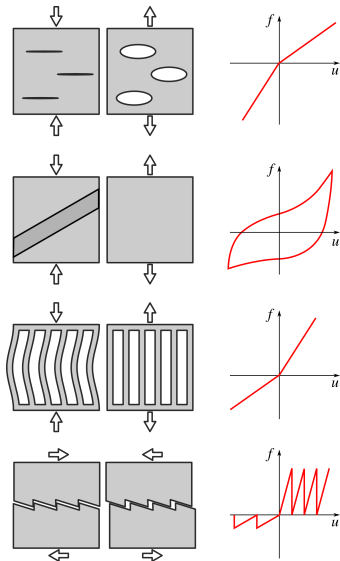
## Sources of asymmetry<sup>[A,B]</sup>:

- Micro-fractures  
*concrete/rocks*
- Local buckling/wrinkling  
*fiber networks, ropes, membranes*
- Phase transformations/twinning  
*Mg alloys, Ti alloys*
- Pressure dependent plasticity  
*concrete/rocks/soils*
- Sliding asymmetry<sup>[C]</sup>  
*patterned surfaces*
- ★ Contacts  
*granular matter, granular crystals*

[A] Ambartsumyan (1965), Izv Academ Nauk USSR Mech

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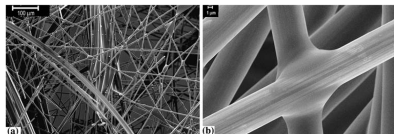


Fig. Carbon fiber network

[1] Mezeix, Bouvet, Huez, Poquillon (2009). J Mater Sci 44

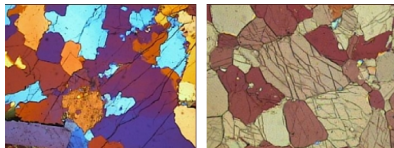


Fig. Microcracks in rocks (dolomite, granite)

[2] Obara (2007). Comput & Geosci 33

[3] Obara, Kozusnikova (2007). Computat Geosci 11



Fig. Torsional instability in multi-strand wires (ropes)

[4] [www.industrialrope.com](http://www.industrialrope.com)



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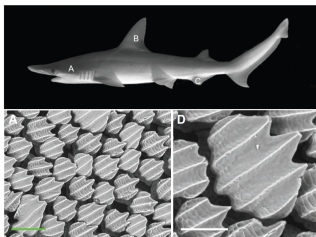


Fig. Shark skin

[5] Wen, Weaver, Lauder (2014). J Exp Biol 217



Fig. Fish-skin pattern on skitour skis

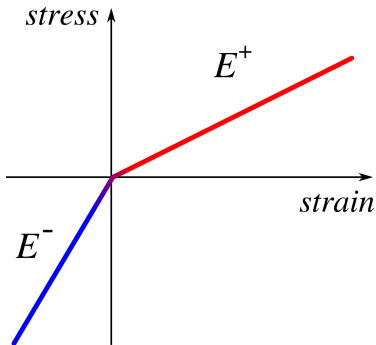
[6] Photo courtesy "Voile"



# Bibliographical sketch

## Hetero-modulus, multi-modulus, bi-modulus

- Sergey A. Ambartsumyan (1965-1969, 1982)
- Robert M. Jones (1971,1975, 1977)
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Elastic properties depend on principal stresses

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix} = \begin{bmatrix} S_{11}(\sigma_1) & S_{12}(\sigma_2) & S_{13}(\sigma_3) \\ S_{21}(\sigma_1) & S_{22}(\sigma_2) & S_{23}(\sigma_3) \\ S_{31}(\sigma_1) & S_{32}(\sigma_2) & S_{33}(\sigma_3) \end{bmatrix} \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \sigma_3 \end{bmatrix}$$

$$S_{11}(+) = S_{22}(+) = S_{33}(+) = \frac{1}{E^+}, \quad S_{11}(-) = S_{22}(-) = S_{33}(-) = \frac{1}{E^-}$$

$$S_{12}(+) = S_{13}(+) = S_{23}(+) = -\frac{\nu^+}{E^+}, \quad S_{12}(-) = S_{13}(-) = S_{23}(-) = -\frac{\nu^-}{E^-}$$

For symmetry

$$\nu^- E^+ = \nu^+ E^-$$

- Adapted variational framework<sup>[1]</sup>.
- Anisotropic damage<sup>[2]</sup>.

[1] Du, Guo (2014). J Mech Phys Solids 73

[2] Desmorat, Gatuingt, Ragueneau (2007). Eng Fract Mech 74



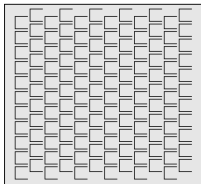
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- Contact as a functional element



# Contact-based architected material

- Contact as a functional element
- **Stiff** in compression / **soft** in tension

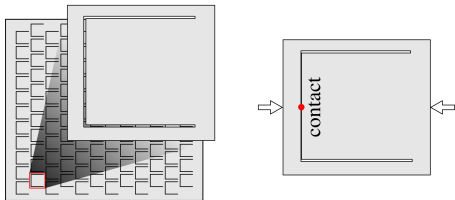






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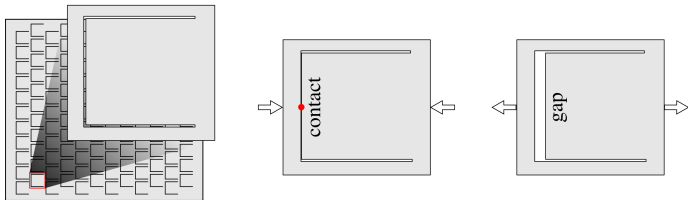
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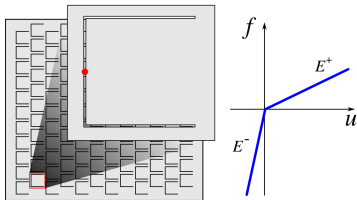
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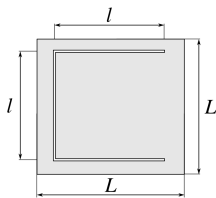
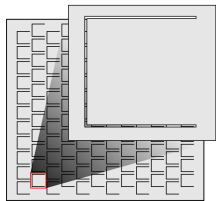
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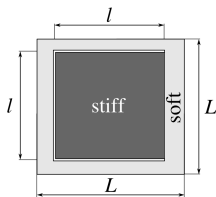
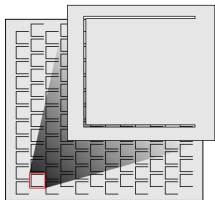


$$E^+/E^- \approx 1 - l/L$$



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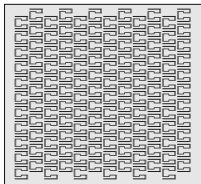


$$E^+ / E^- \approx (1 - l/L) E^{\text{soft}} / E^{\text{stiff}}$$



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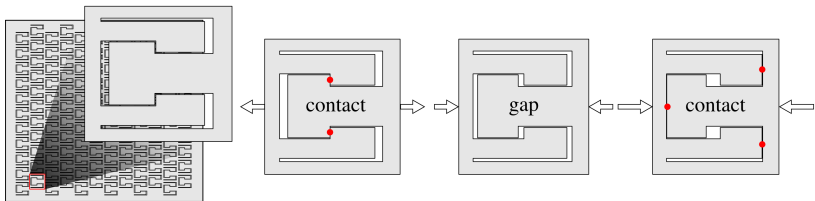
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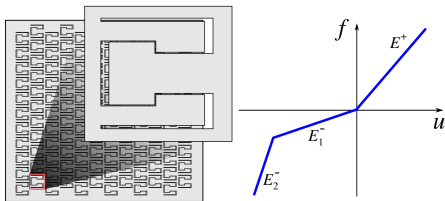
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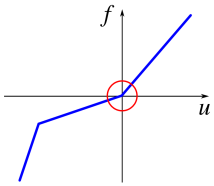
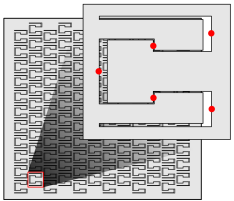
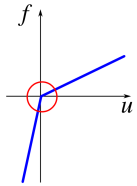
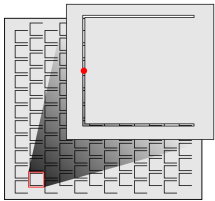






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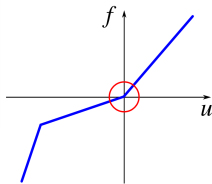
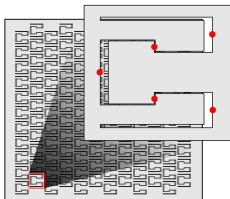
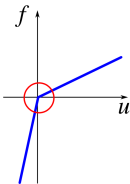
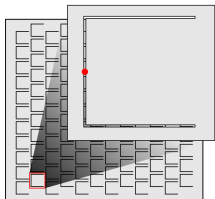
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# Contact-based architected material

- Contact as a functional element
- **Stiff** in compression / **soft** in tension
- Use different materials
- **Soft** in compression/**stiff** in tension
- Extendable to 3D





# Stiff-in-tension / soft-in-compression: example

- Tension/compression test (FE simulation)



# Governing equation for asymmetric materials

- Quasistatic 1D behavior:

$$\sigma = E(\nabla u + \alpha|\nabla u|) = \begin{cases} (1 + \alpha)E\nabla u, & \text{if } \nabla u > 0, \text{ tension} \\ (1 - \alpha)E\nabla u, & \text{if } \nabla u \leq 0, \text{ compres.} \end{cases}, \quad -1 < \alpha < 1$$

- Elastic contrast  $\gamma$ :

$$\frac{E^+}{E^-} = \frac{1 + \alpha}{1 - \alpha} = \gamma$$

- Elastodynamic equation in 1D (the simplest approximation):

$$\rho \ddot{u} = E \nabla (\nabla u + \alpha|\nabla u|) + \underbrace{\mu \Delta u}_{\text{damping}}$$

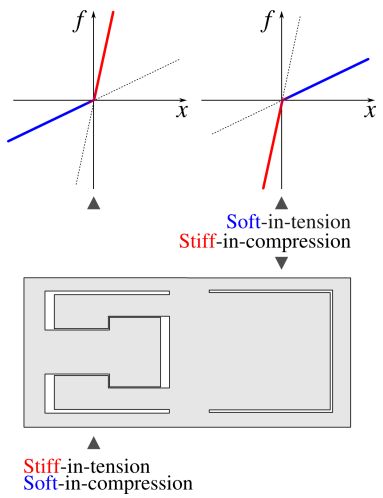
- Wave celerity  $c$ :

$$c = \begin{cases} \sqrt{(1 + \alpha)E/\rho}, & \text{if } \nabla u > 0, \text{ tension} \\ \sqrt{(1 - \alpha)E/\rho}, & \text{if } \nabla u \leq 0, \text{ compres.} \end{cases}, \quad \frac{c^+}{c^-} = \sqrt{\frac{1 + \alpha}{1 - \alpha}} = \sqrt{\gamma}$$



# Set-up and simplified model

- Adjust elastic properties
- Combine in a quasi-statically symmetric element





# Set-up and simplified model

- Adjust elastic properties
- Combine in a quasi-statically symmetric element
- Simplify

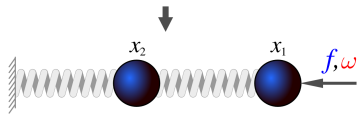
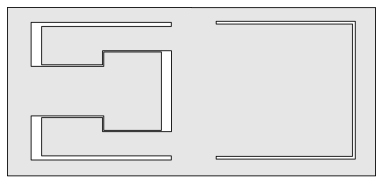
$$k^{\text{soft}} = \frac{E^{\text{soft}} A}{L}, \quad k^{\text{stiff}} = \frac{E^{\text{stiff}} A}{L}, \quad \gamma = \frac{k^{\text{stiff}}}{k^{\text{soft}}}$$

$$k_{\text{spring}}^{\text{eff}} = \frac{2\gamma}{1 + \gamma} k^{\text{soft}}$$

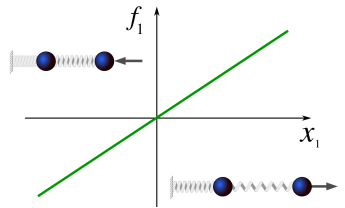
$$\ddot{X} + 2\eta C \dot{X} + k^{\text{soft}} K(X) X = F$$

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad F = \begin{bmatrix} \sin(\omega t + \phi) \\ 0 \end{bmatrix},$$

$$K = \begin{bmatrix} \beta(x_1 - x_2) & -\beta(x_1 - x_2) \\ -\beta(x_1 - x_2) & \beta(x_1 - x_2) + \beta(-x_2) \end{bmatrix}$$



+ damping





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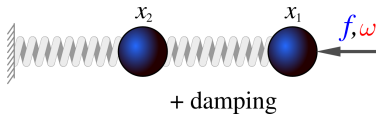
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$$\beta(x) = \begin{cases} \gamma, & \text{if } x < 0; \\ 1, & \text{if } x \geq 0. \end{cases}$$

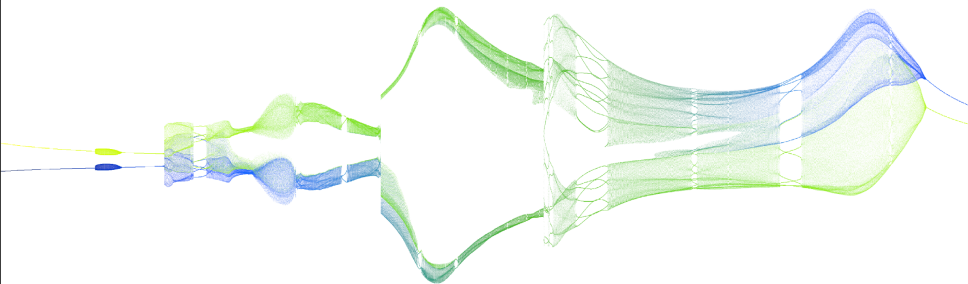
- Tens-tens / comp-comp

$$K_{tt} = \begin{bmatrix} 1 & -1 \\ -1 & 1 + \gamma \end{bmatrix}, \quad K_{cc} = \begin{bmatrix} \gamma & -\gamma \\ -\gamma & 1 + \gamma \end{bmatrix}$$

- Tens-comp / comp-tens

$$K_{tc} = \begin{bmatrix} 1 & -1 \\ -1 & 2 \end{bmatrix}, \quad K_{ct} = \begin{bmatrix} \gamma & -\gamma \\ -\gamma & 2\gamma \end{bmatrix},$$

## Forced oscillations







# Analysis principle

## System of equations

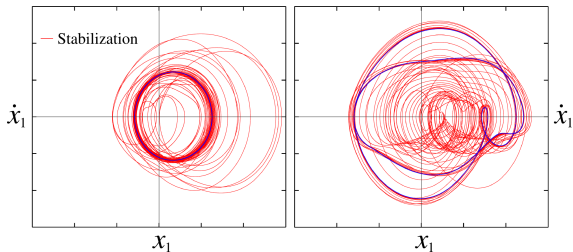
$$\ddot{X} + 2\eta C\dot{X} + K(X, \gamma)X = F(\omega)$$

## Parameters:

- damping  $\eta \in [0.01; 0.2]$  in 10 steps
- stiffness contrast  $\gamma \in [1; 5]$  in 800 steps
- forcing frequency  $\omega \in [0.1, 7.0]$  in 10 000 steps

## Track:

- Stable cycle



\*Poincaré point:  $\{x_1, \dot{x}_1\}$  for  $\omega t = 2\pi n$



# Analysis principle

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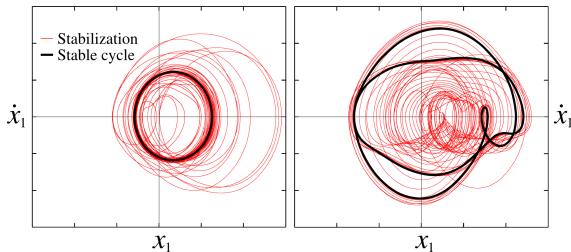
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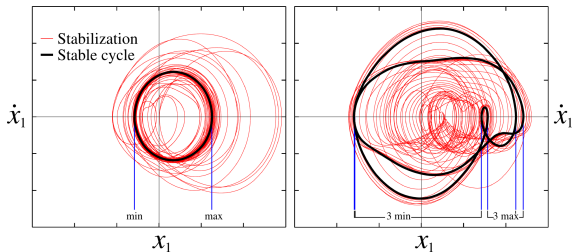
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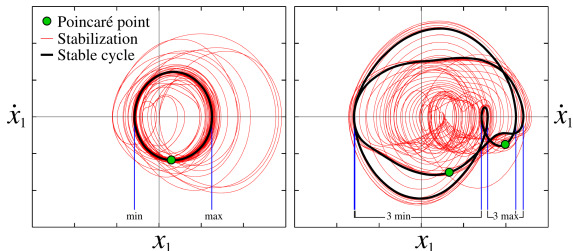
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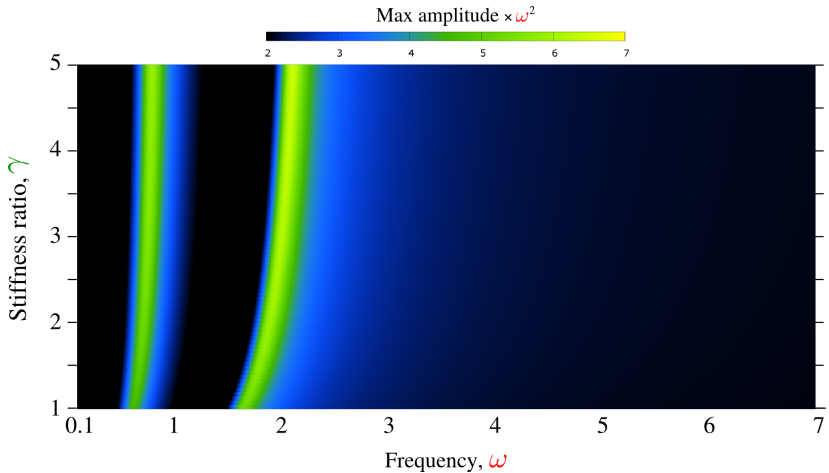
- Stable cycle
- Min/max amplitude
- Number of amplitude extrema
- Number of Poincaré points\*



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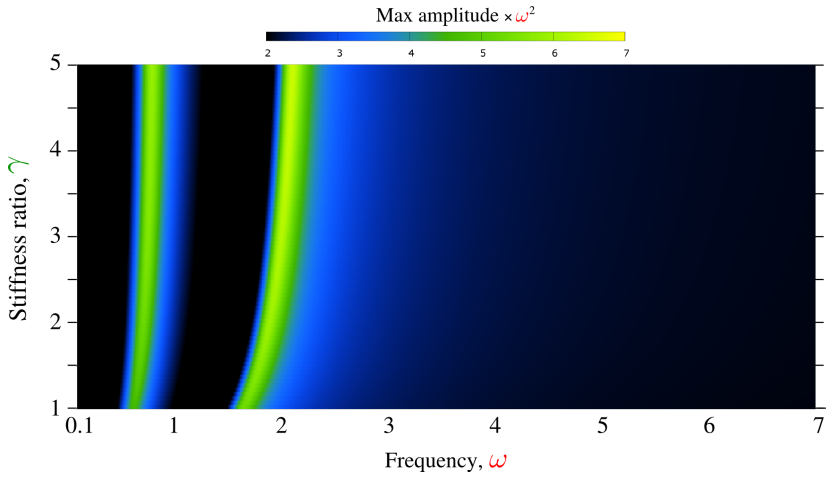
# Homogenized model



- One maximum, one minimum, one Poincaré point.

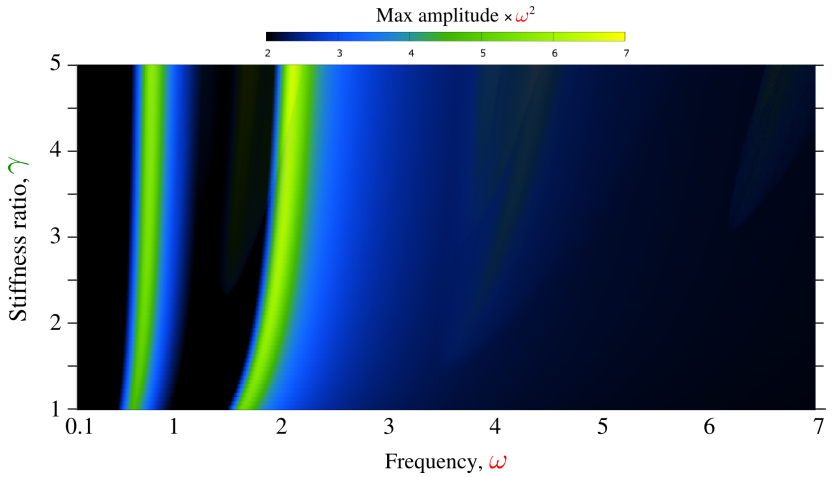


# Bimodulus system $\alpha = 0.1$



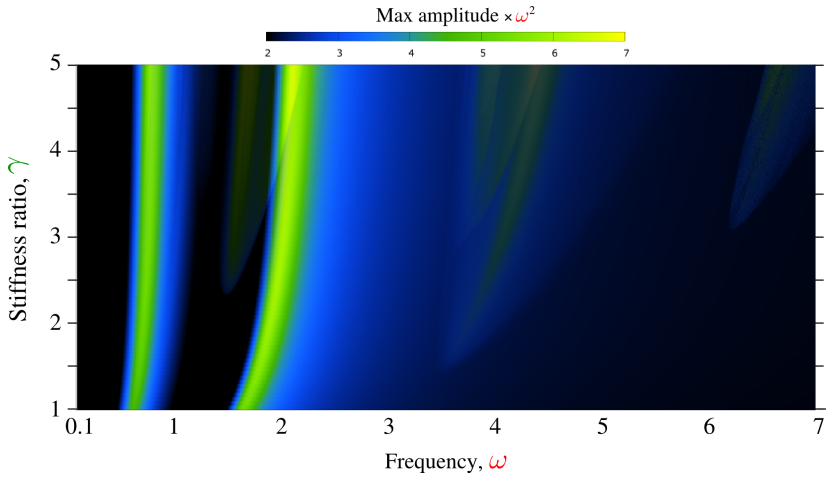


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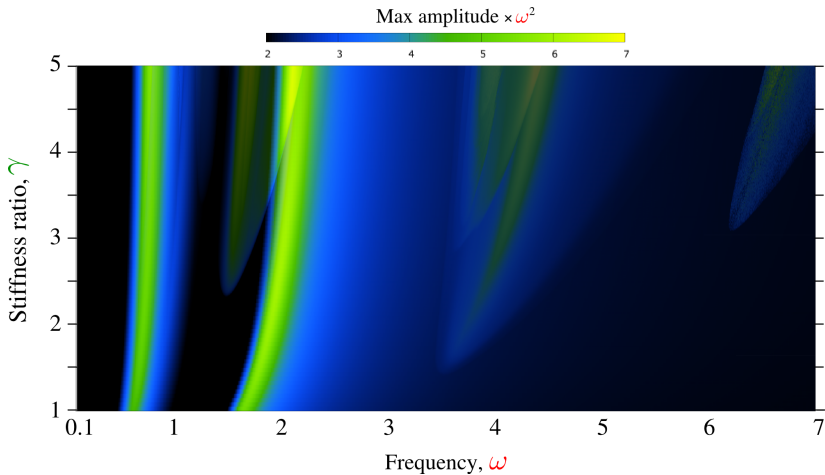
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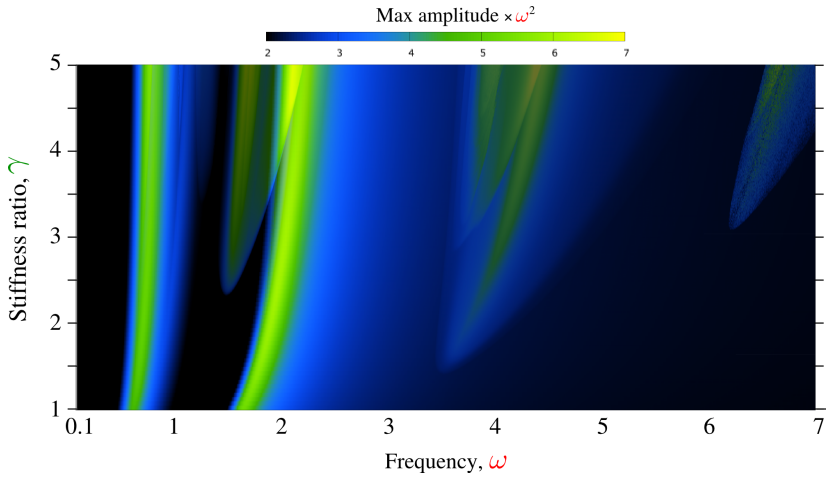


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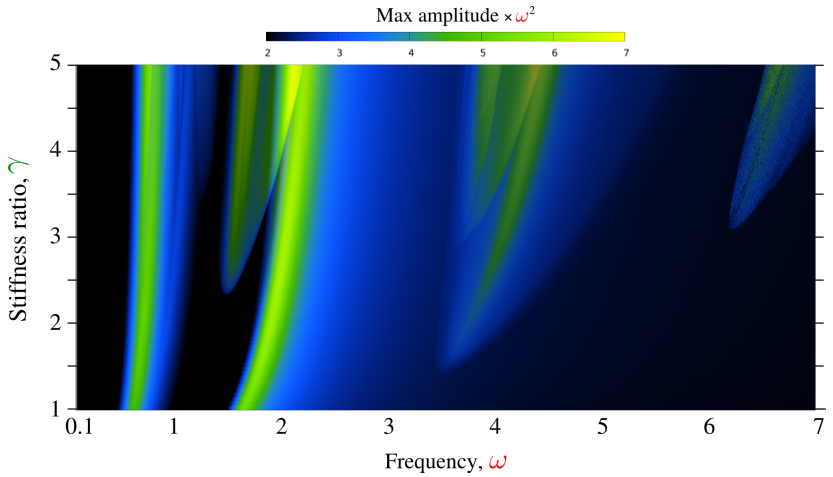


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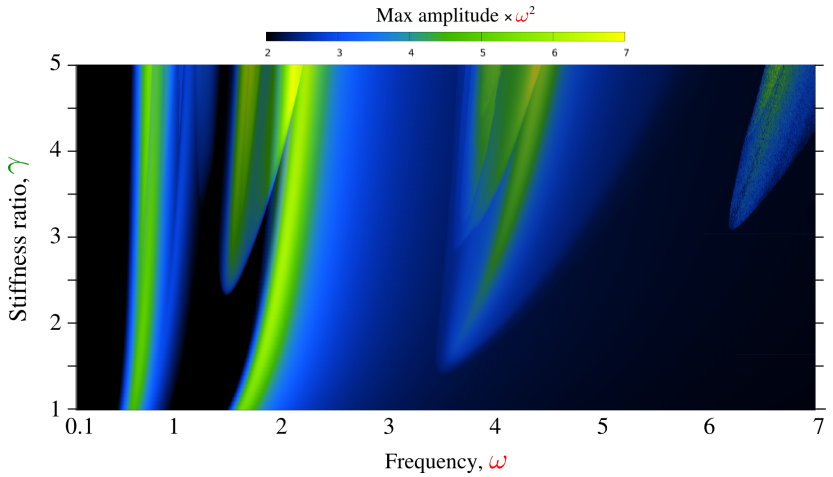


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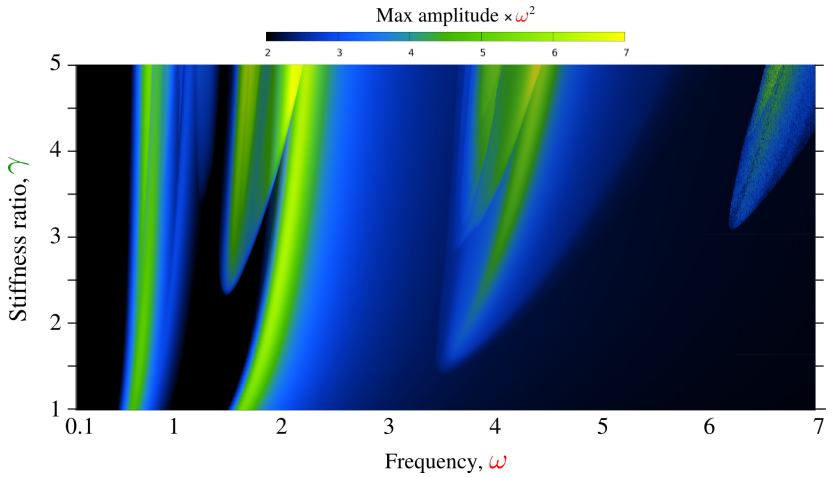


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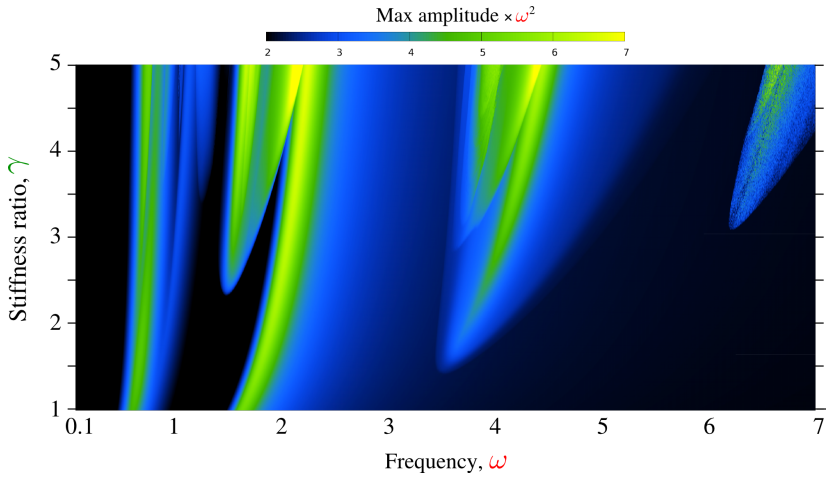


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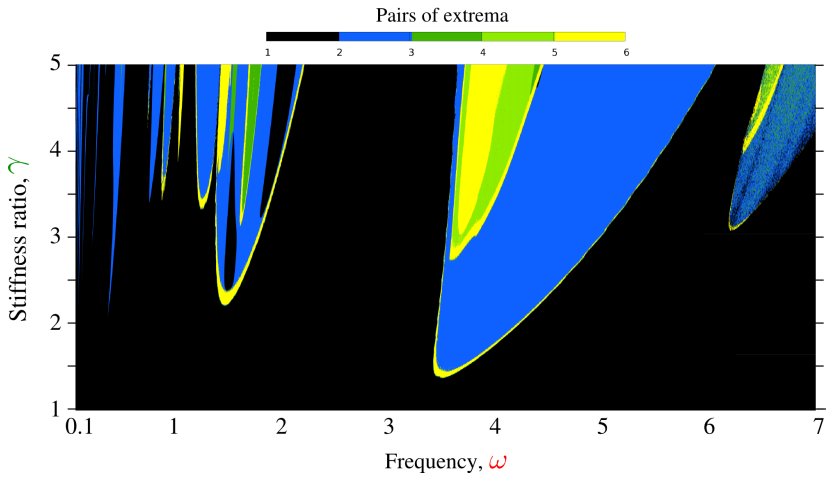


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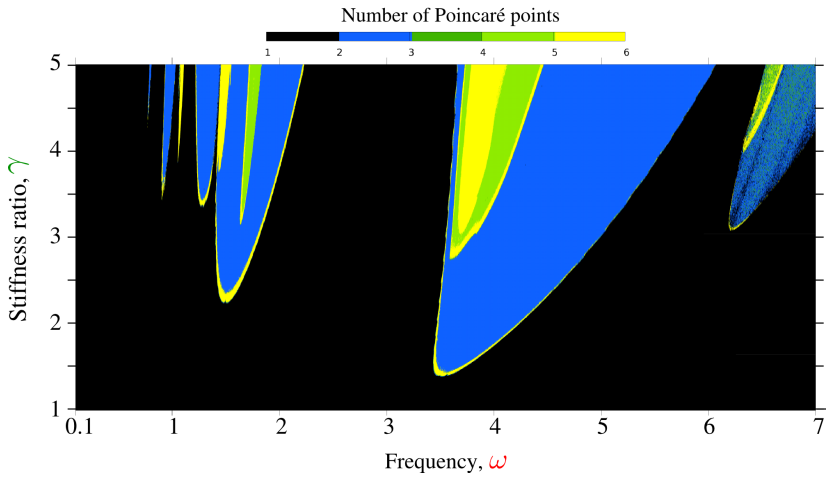


# Bimodulus system $\alpha = 0.1$





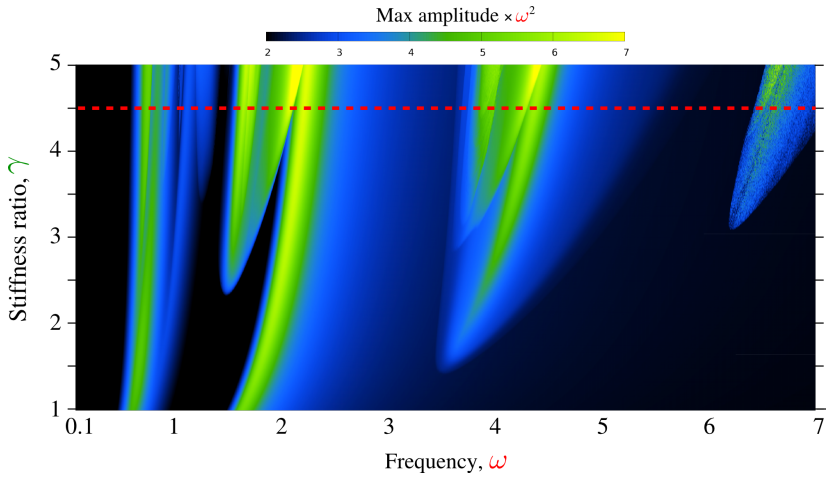
# Bimodulus system $\alpha = 0.1$





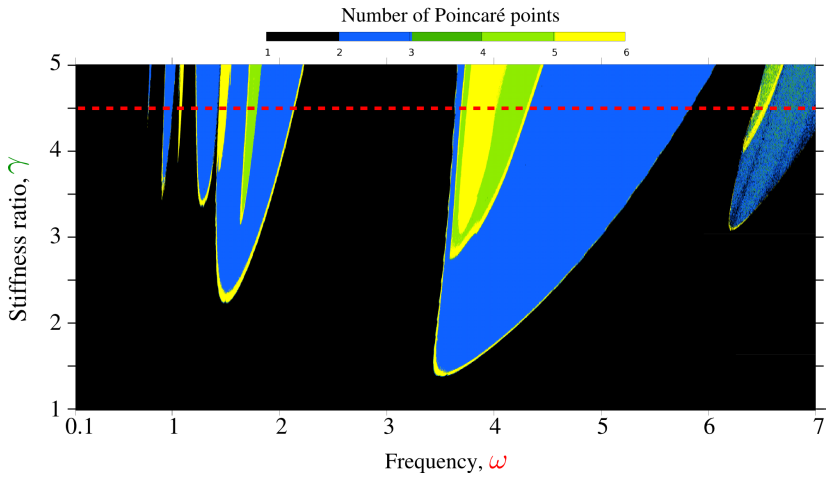


# Bimodulus system $\alpha = 0.1$ : dive in the plot



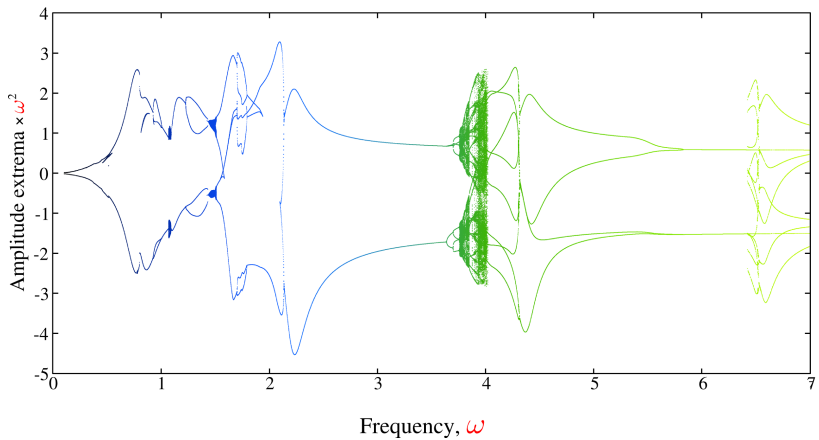


# Bimodulus system $\alpha = 0.1$ : dive in the plot



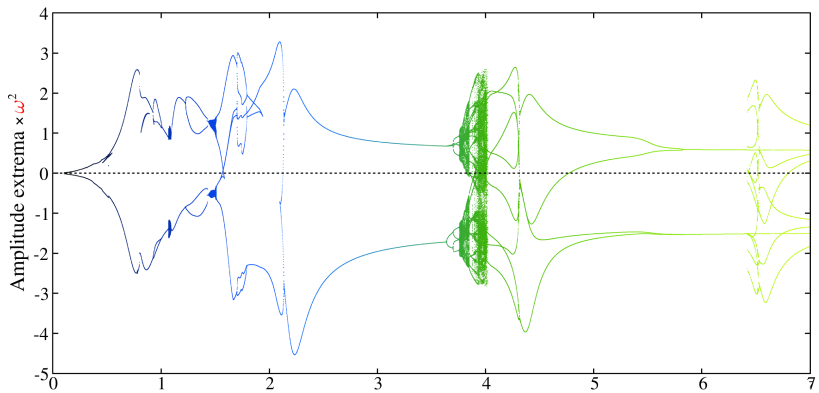


# Bimodulus system $\alpha = 0.1$ : dive in the plot





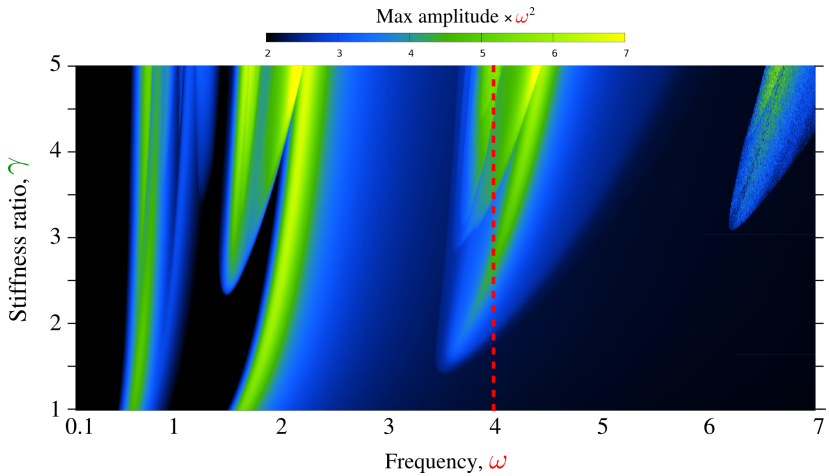
# Bimodulus system $\alpha = 0.1$ : dive in the plot



● Asymmetrical oscillations

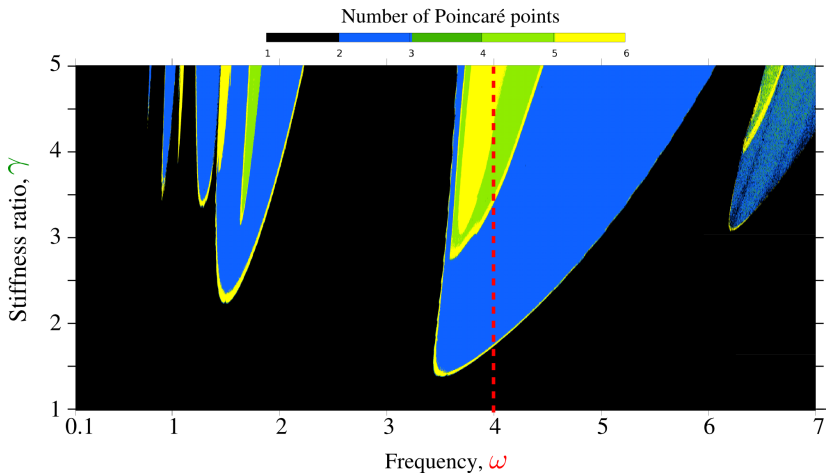


# Bimodulus system $\alpha = 0.1$ : dive in the plot II



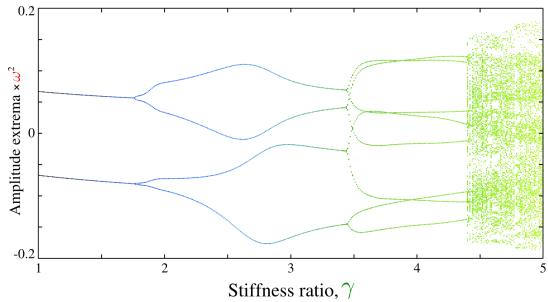


# Bimodulus system $\alpha = 0.1$ : dive in the plot II



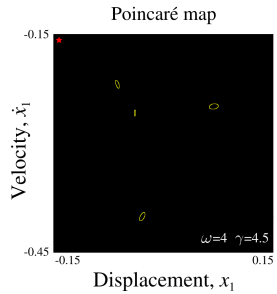
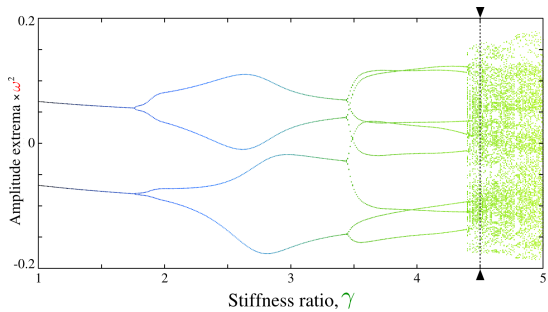


# Bimodulus system $\alpha = 0.1$ : dive in the plot II





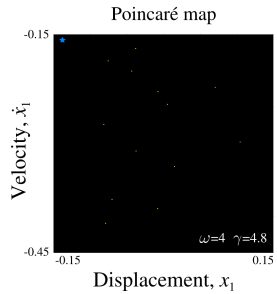
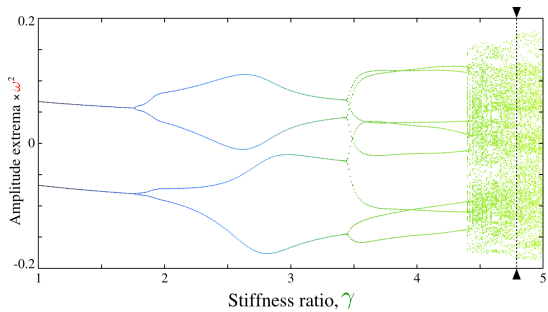
# Bimodulus system $\alpha = 0.1$ : dive in the plot II





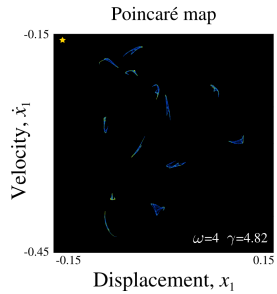
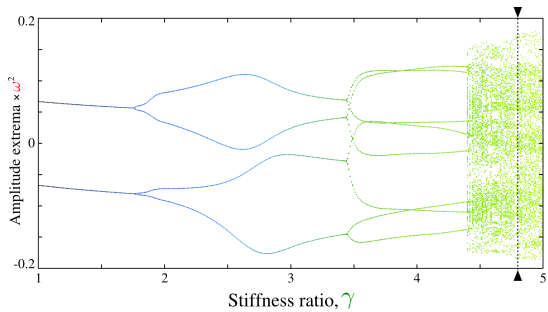


# Bimodulus system $\alpha = 0.1$ : dive in the plot II



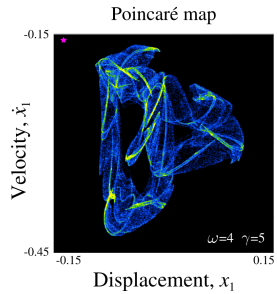
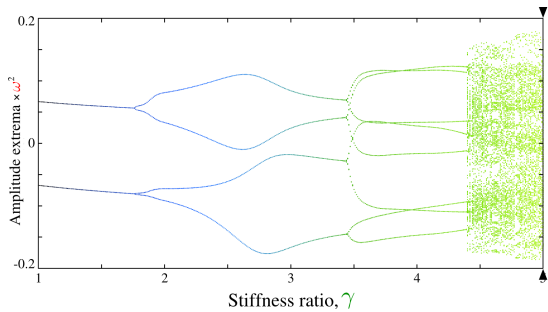


# Bimodulus system $\alpha = 0.1$ : dive in the plot II





# Bimodulus system $\alpha = 0.1$ : dive in the plot II

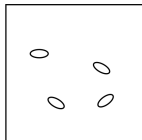


Vizualise in 4D

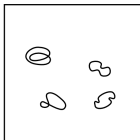


# Transition to chaos: mechanism

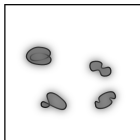
Projection of 4D phase portraits on 2D



Multiple Hopf loops



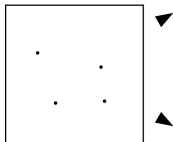
Perturbed loops



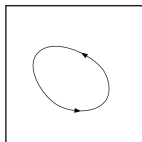
Localised strange attractors



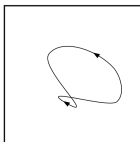
Compact strange attractor



Period doubling



Single Hopf loop



Perturbed loop

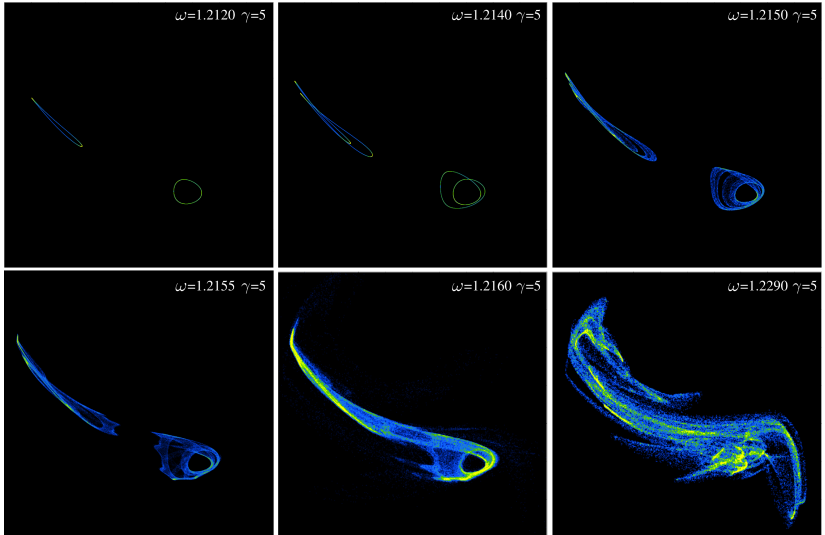


Compact strange attractor

[8] Natsiavas (1993), J Sound Vib 165



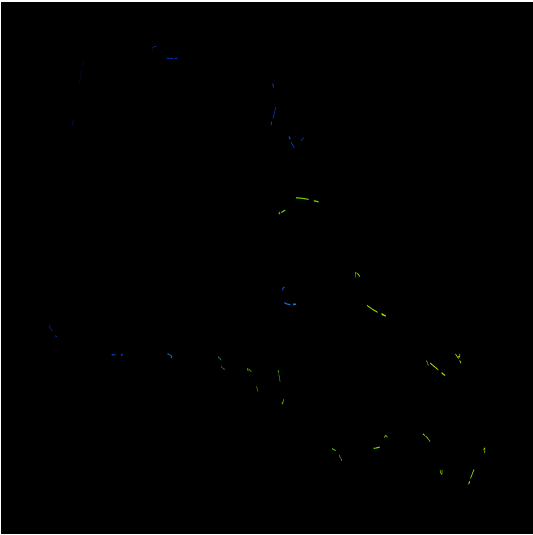
# Transition to chaos: example



Vizualise in 4D

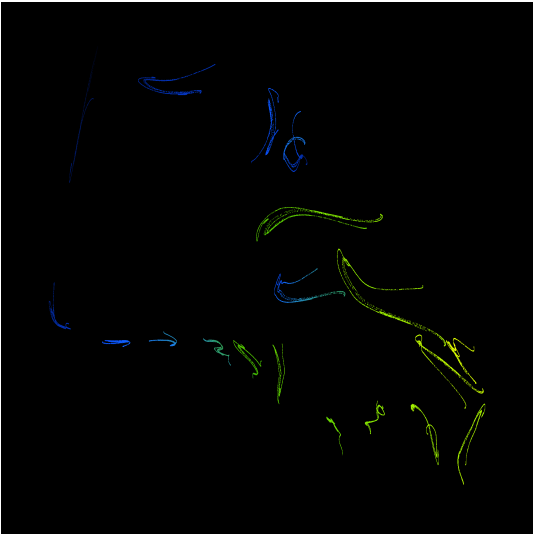


# Transition to chaos: example 2



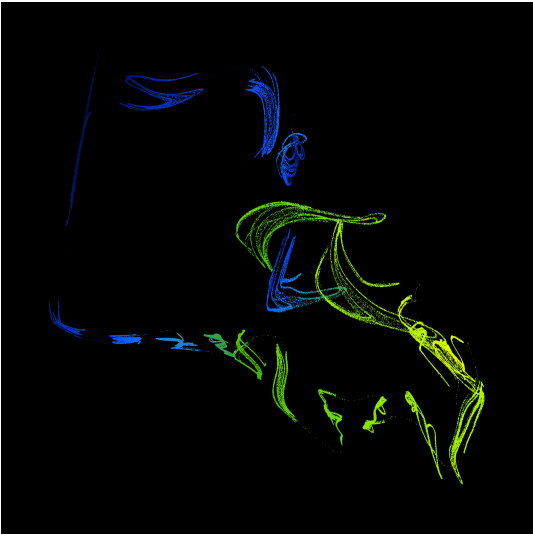


# Transition to chaos: example 2





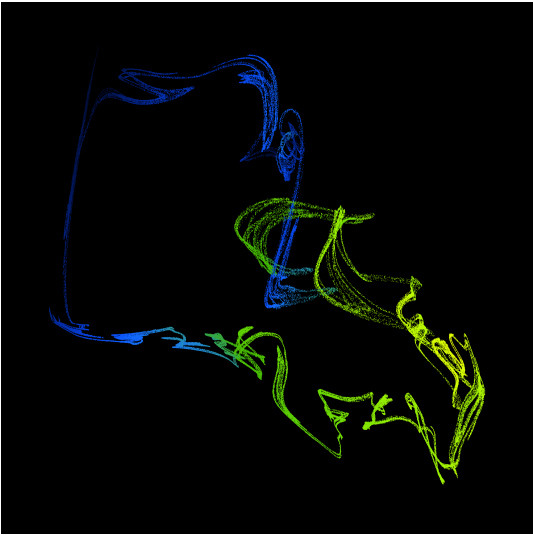
# Transition to chaos: example 2







# Transition to chaos: example 2



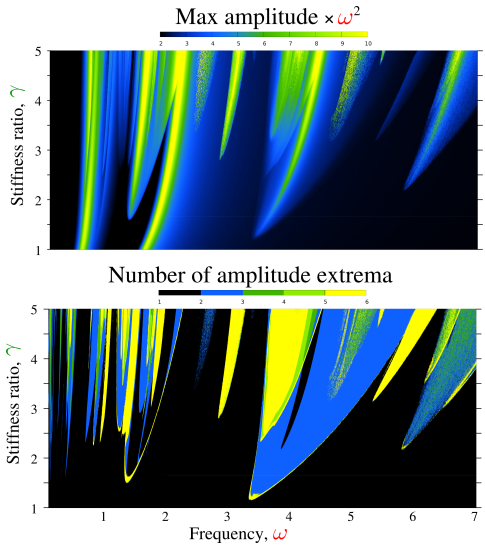


# Strange attractors in 4D

Examples of 4D strange attractor projected on 3D  $(x_1, \dot{x}_1, x_2, \dot{x}_2)$ , the color represents the 4th dimension



# Lighter damping

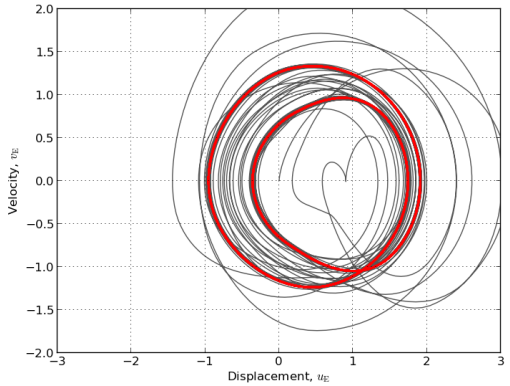


A diagram of an Artificial Neural Network (ANN) showing a complex network of interconnected nodes. The nodes are represented by circles of various colors: grey, yellow, green, and light blue. The connections are shown as lines between the nodes. A central black box with yellow text reads "Artificial Neural Network". The network is organized into layers, with nodes in each layer connected to nodes in the adjacent layers. The overall structure is a dense, interconnected web of nodes and edges, with some nodes having more connections than others. The nodes are arranged in a roughly rectangular pattern, with some nodes at the top and bottom edges. The connections are mostly horizontal and vertical, with some diagonal lines. The nodes are connected in a way that suggests a flow of information from left to right. The central black box is positioned in the middle of the network, with the text "Artificial Neural Network" written in a bold, yellow, sans-serif font. The background is white, and the nodes and connections are drawn in black and colored circles. The overall appearance is that of a technical diagram illustrating the structure of an ANN.

**Artificial Neural Network**



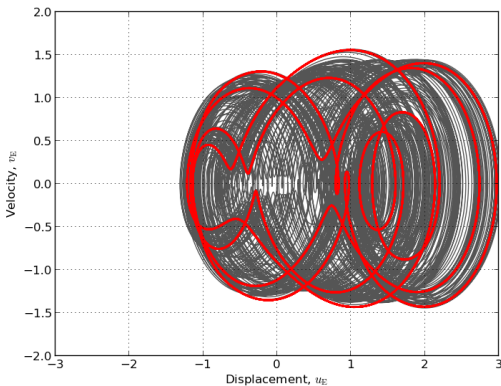
# Motivation



Sometimes finding the limit cycle is fast



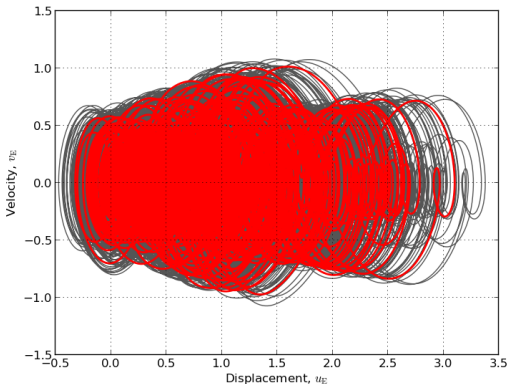
# Motivation



Sometimes the stabilisation takes longer time:  
simulation of thousands load cycles is needed



# Motivation



Sometimes there's no limit cycle: chaotic regime  
To be sure that it's chaotic, millions(!) of cycles should be simulated



# Motivation

Could we train an Artificial Neural Network (ANN) to  
predict  
the regime of oscillations?





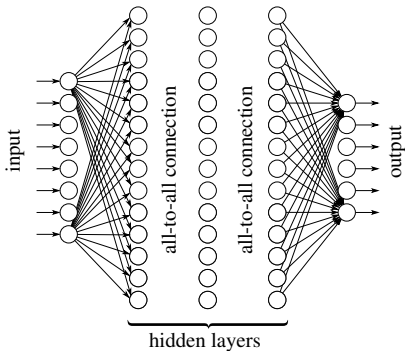
# Objectives & means

## Objectives:

- 1 Forecast dynamics without full information about the system
- 2 Forecast vibration regime (simple, multi-period, quasiperiodic, chaotic)

## Means:

- 1 Multilayer Perceptron with ReLU (Rectified Linear Unit)



- Layer to layer formula

$$X^{i+1} = f(W^{i,i+1}X^i + B^i)$$

$W^{i,i+1}$  matrix of weights,  
 $B^i$  vector of biases.

- ReLU

$$f(x) = \begin{cases} 0, & \text{if } x < 0; \\ x, & \text{if } x \geq 0. \end{cases}$$

- Least mean squared error,  
backpropagation



# Architectures

## ■ Input/output:

- Independent ANN for velocity and displacement

input:  $\{X^{k+i}, i \in [1, 100]\}$

output:  $\{X^{k+100+j}, j \in [1, 50]\}$

- Single ANN for both velocity and displacement

input:  $\{X^{k+i}, V^{k+i}, i \in [1, 100]\}$

output:  $\{X^{k+100+j}, V^{k+100+j}, j \in [1, 50]\}$

## ■ Architectures:

Inp time points  $\rightarrow$  Hidden Layer  $\rightarrow$  Hidden Layer  $\rightarrow \dots \rightarrow$  Out time points

- One hidden layer:  $2 \times 100 \rightarrow 1000 \rightarrow 2 \times 50$
- Two hidden layers:  $2 \times 100 \rightarrow 500 \rightarrow 200 \rightarrow 2 \times 50$
- Three hidden layers:  $100 \rightarrow \underbrace{100 \rightarrow 75 \rightarrow 50}_{\text{Hidden layers}} \rightarrow 50$

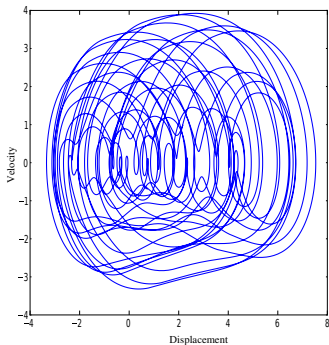
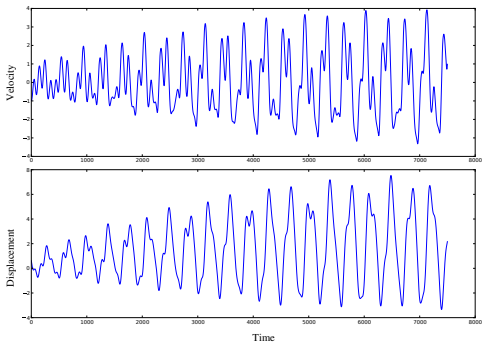
- Three hidden layers:  $2 \times 100 \rightarrow \underbrace{200 \rightarrow 150 \rightarrow 100}_{\text{Hidden layers}} \rightarrow 2 \times 50$

- etc ...



# Objective 1: forecasting

## Training



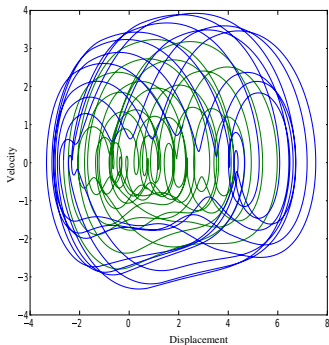
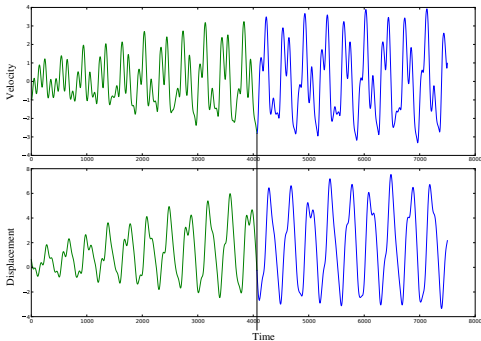
## Forecasting

- Within training interval
- Outside training interval



# Objective 1: forecasting

## Training



In total 100 cycles simulated: 50 cycles for training, 50 for verification

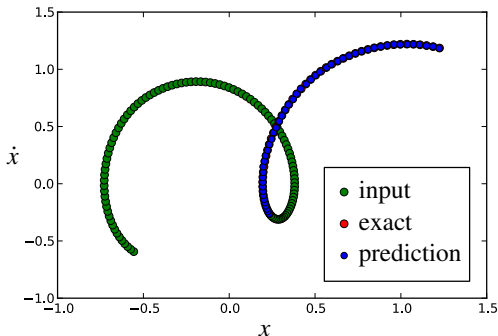
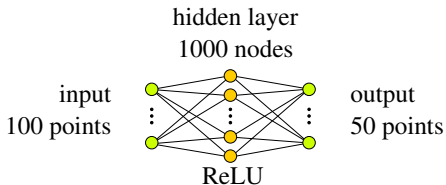
## Forecasting

- Within training interval
- Outside training interval



# Results I

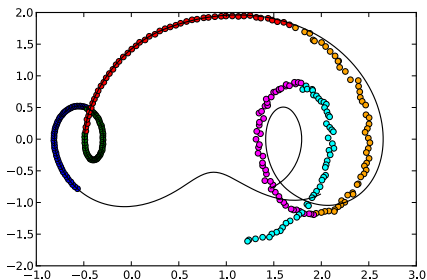
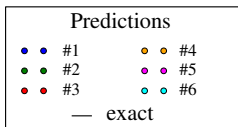
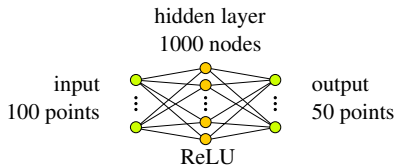
Single layer: complexity  $200 \times 1000 + 1000 \times 100 = 3 \cdot 10^5$





# Results I

Single layer: complexity  $200 \times 1000 + 1000 \times 100 = 3 \cdot 10^5$

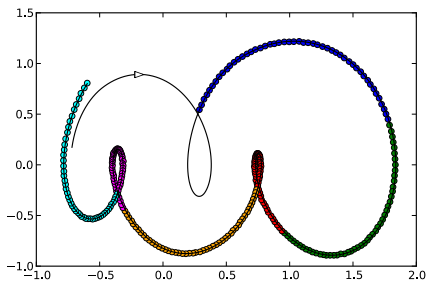
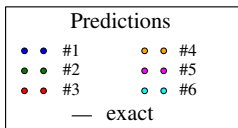
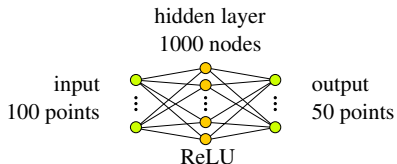


Six predictions



# Results I

Single layer: complexity  $200 \times 1000 + 1000 \times 100 = 3 \cdot 10^5$

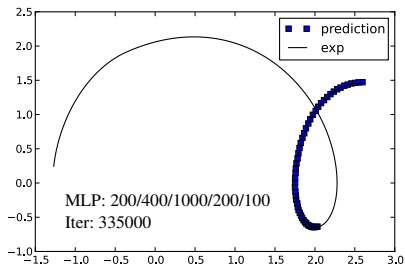
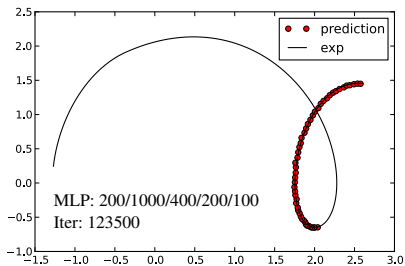


Sinx predictions (reinforced convergence tolerance)



## Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$



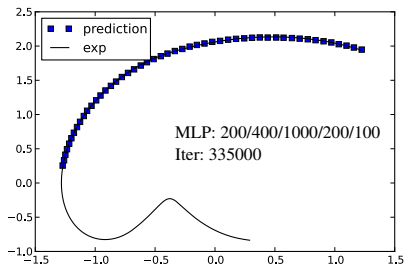
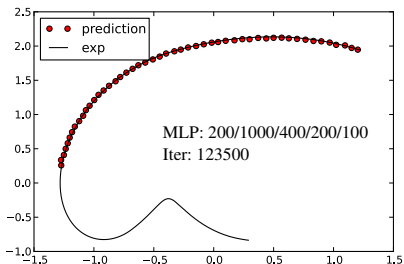
Within training domain





# Results II: inside vs outside training domain

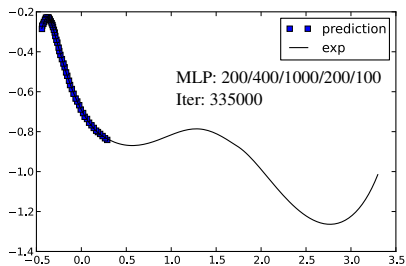
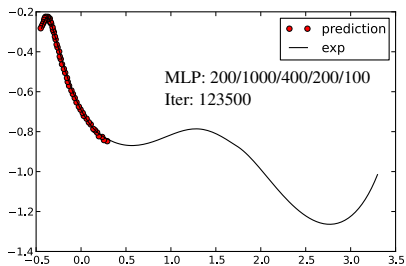
Three layers: complexity  $7 \cdot 10^5$



Within training domain

# Results II: inside vs outside training domain

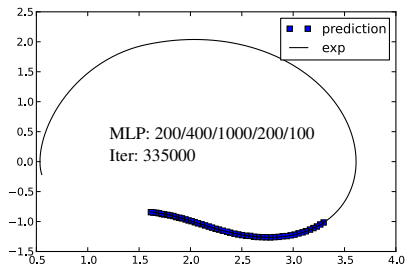
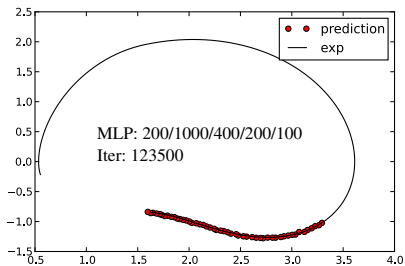
Three layers: complexity  $7 \cdot 10^5$



Within training domain

# Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$

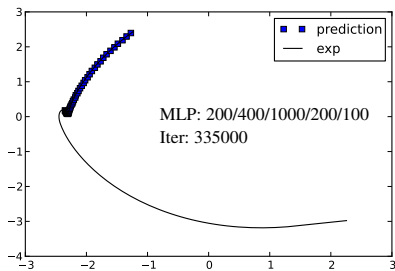
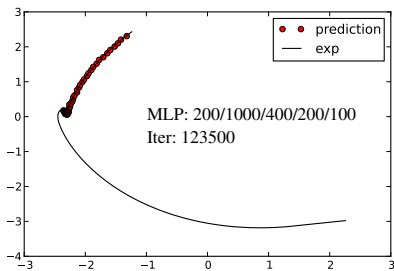


Within training domain



# Results II: inside vs outside training domain

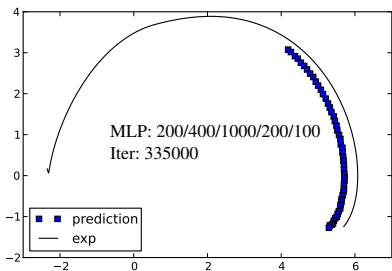
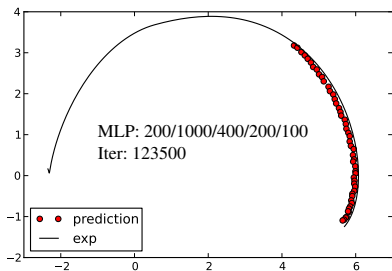
Three layers: complexity  $7 \cdot 10^5$



Outside training domain

# Results II: inside vs outside training domain

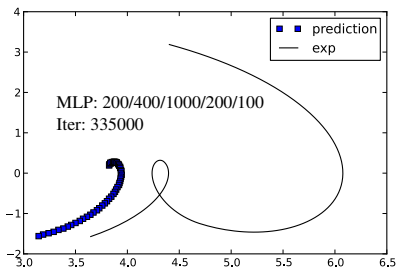
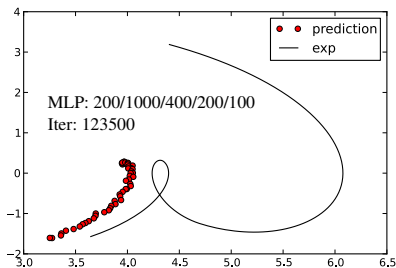
Three layers: complexity  $7 \cdot 10^5$



Outside training domain

# Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$

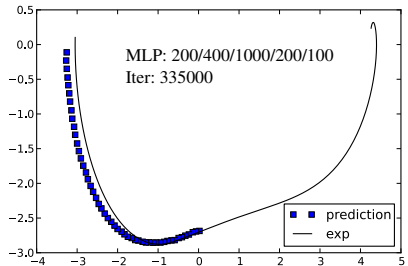
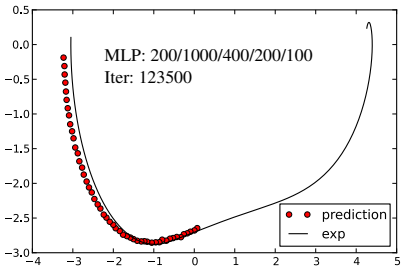


Outside training domain



# Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$

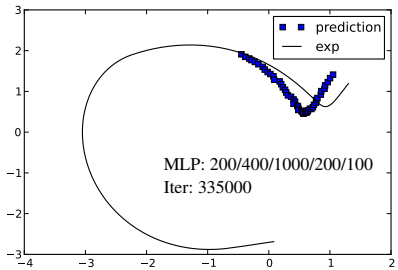
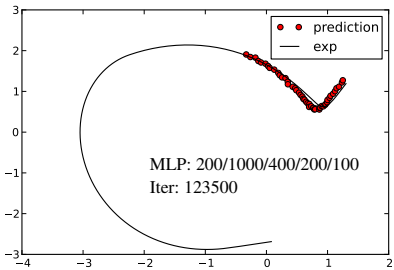


Outside training domain



# Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$



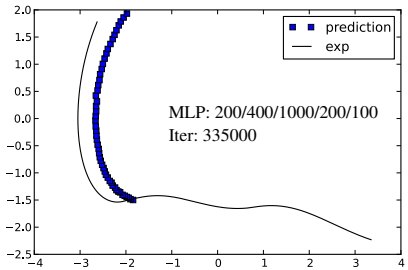
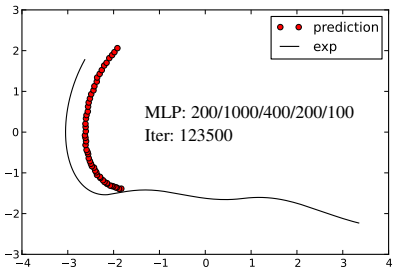
Outside training domain





# Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$

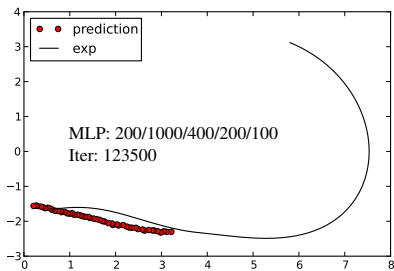


Outside training domain

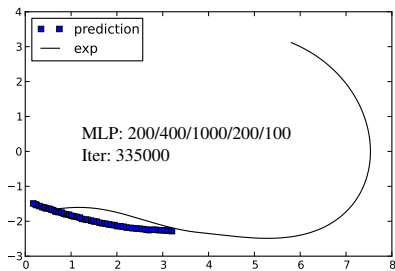


## Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$



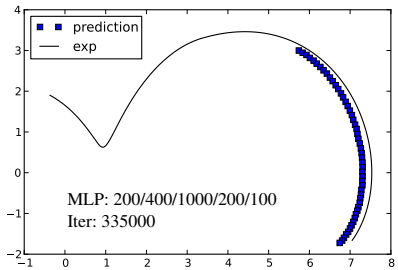
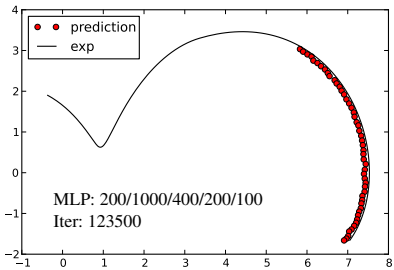
Outside training domain





# Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$

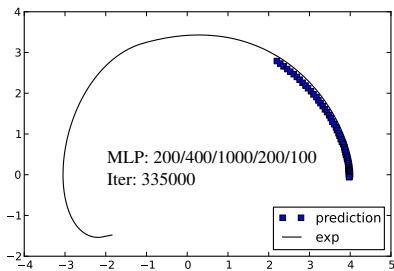
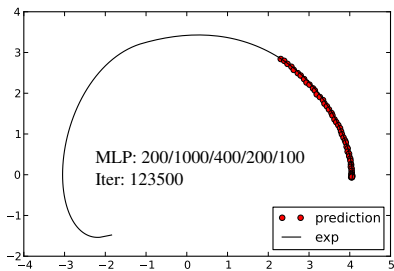


Outside training domain



# Results II: inside vs outside training domain

Three layers: complexity  $7 \cdot 10^5$

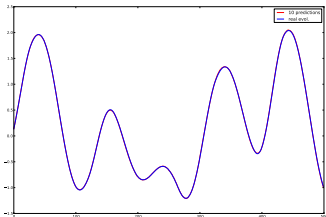


Outside training domain

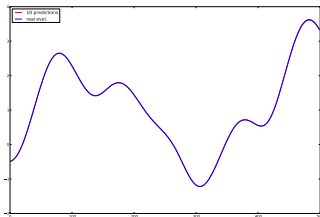


# Results III: Simplified architecture

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$



Velocity



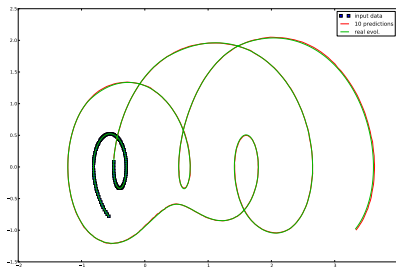
Displacement

10 predictions within training domain



## Results III: Simplified architecture

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$

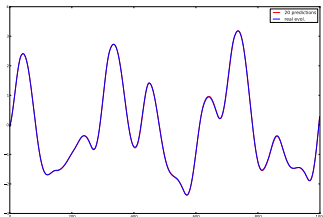


10 predictions within training domain

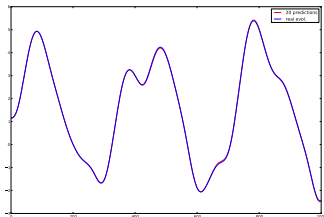


# Results III: Simplified architecture

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$



Velocity



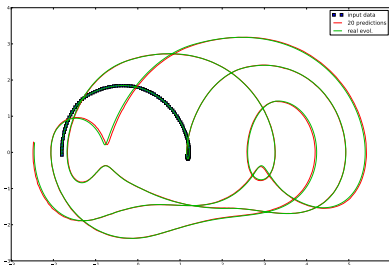
Displacement

20 predictions within training domain



## Results III: Simplified architecture

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$



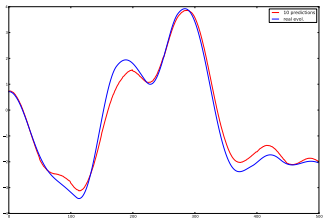
10 predictions within training domain



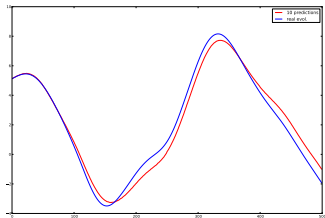


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Velocity



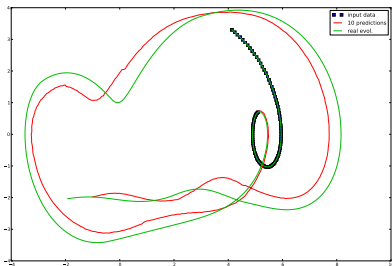
Displacement

10 predictions **outside** training domain



## Results III: Simplified architecture

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$

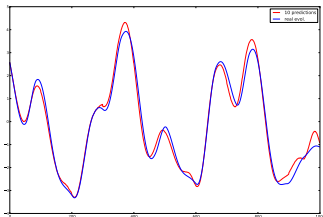


10 predictions **outside** training domain

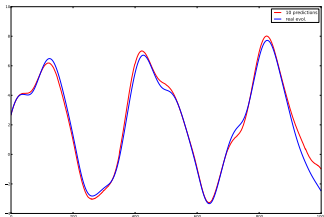


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Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$



Velocity



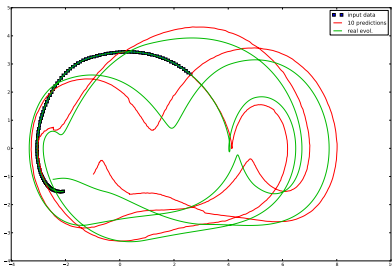
Displacement

20 predictions **outside** training domain



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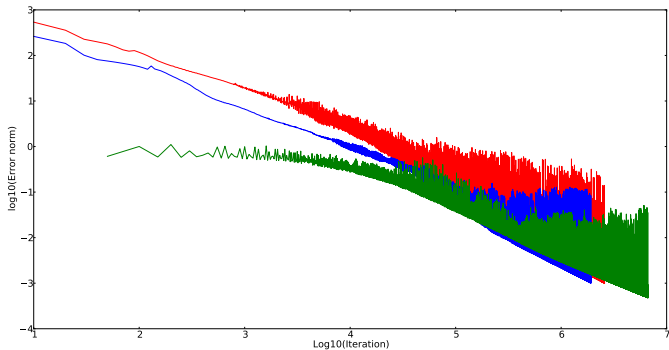


20 predictions **outside** training domain



# Results III: Simplified architecture

Three layers: 200 → 100 → 100 → 100 → 100, complexity  $5 \cdot 10^4$

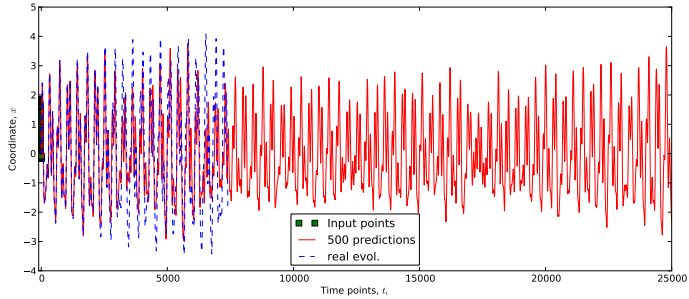


Convergence for different learning rates



# Results IV: go futher in prediction

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$

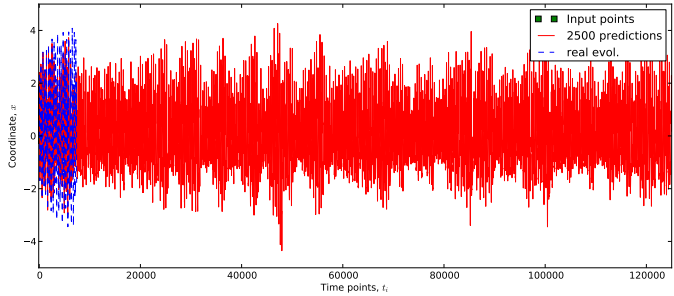


500 predictions from the inside of the training domain



# Results IV: go futher in prediction

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$

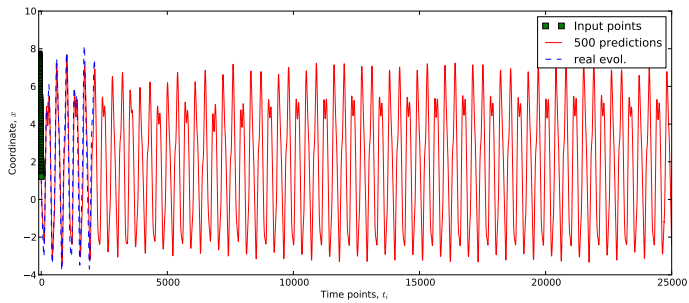


2500 predictions from the inside of the training domain



# Results IV: go futher in prediction

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$



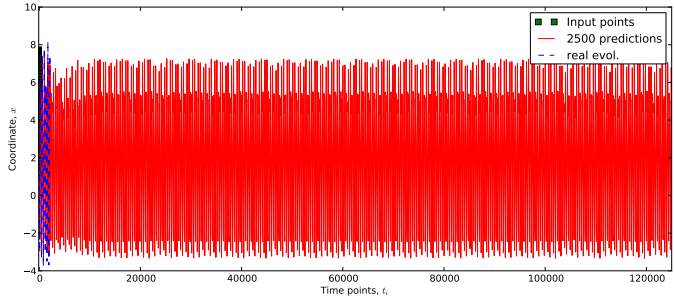
500 predictions from the inside of the training domain





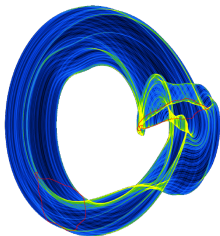
# Results IV: go futher in prediction

Three layers:  $200 \rightarrow 100 \rightarrow 100 \rightarrow 100 \rightarrow 100$ , complexity  $5 \cdot 10^4$



2500 predictions from the inside of the training domain

## Conclusions & perspectives





# Conclusions and perspectives

## First results

- To some extent we can forecast complex dynamics accurately within the training domain, less accurately outside it.
- However, we trained our ANN only for a single frequency

## Perspectives

- Predicting dynamics for arbitrary frequency seems too difficult, hm?  
Too much training data and time is needed.
- Classification of regimes for arbitrary frequency seems quite difficult



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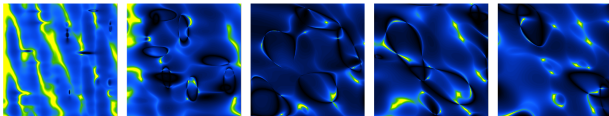
Thank you for your attention!

**Merci de votre attention !**

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## Computational approach





# Computational strategies

## Integration

- 1** Direct integration (explicit/implicit)
    - Störmer-Verlet integration (lacks precision)
  - 2** Semi-analytical integration
    - Newton method to solve homogeneous problem
    - Newton method to identify switch between regimes
    - Adapt time step to match  $2\pi/\omega$
- *A few regimes with constant coefficients*
  - *Thus they are integrable semi-analytically*

## Results

- Random assignment of initial conditions
- Periodicity: check history of Poincaré points (depth  $2^n$ )
- Particular treatment of chaotic regimes