Exploring experimental physics with machine learning…

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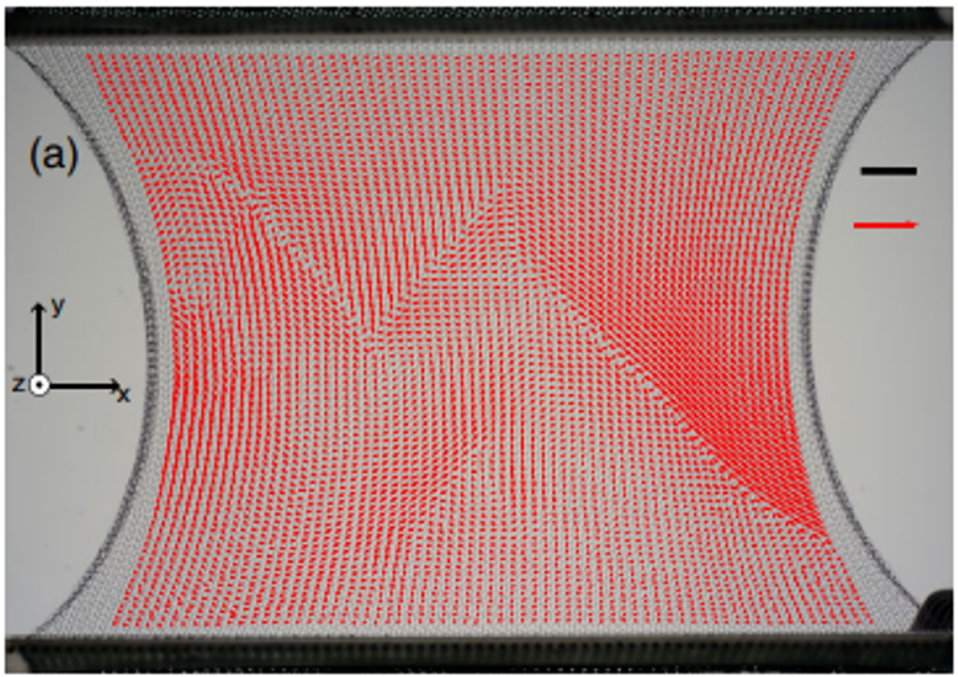
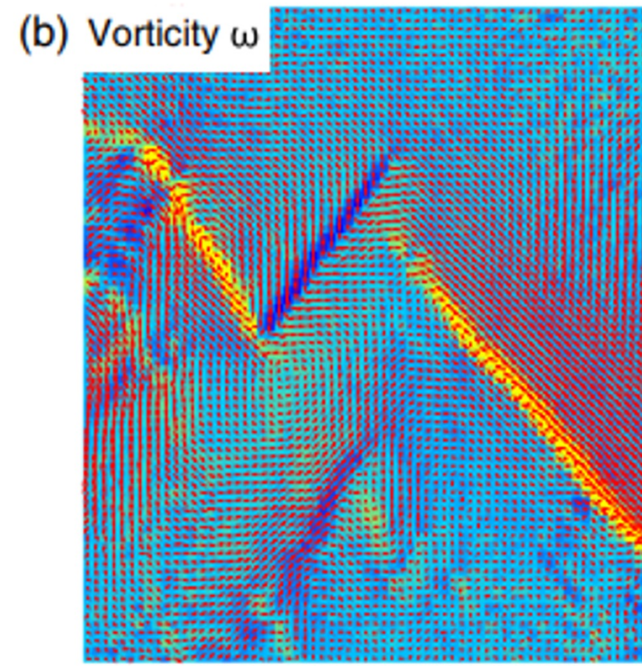
Workshop GDR IDE, Les Houches, 5/04/2023

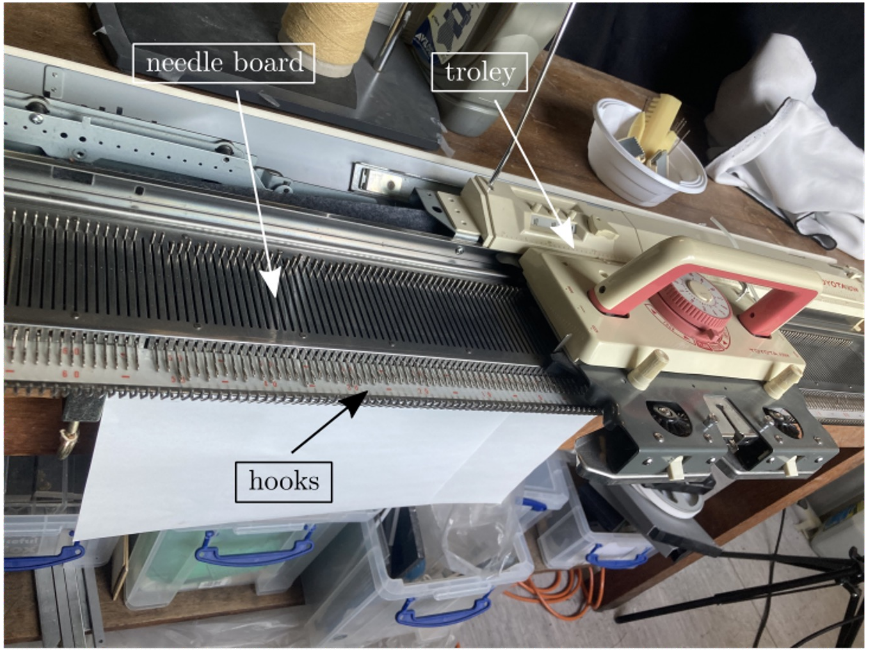
Seismic Events Prediction in Knitted Fabric through Deep Learning

Poincloux & al. 2018





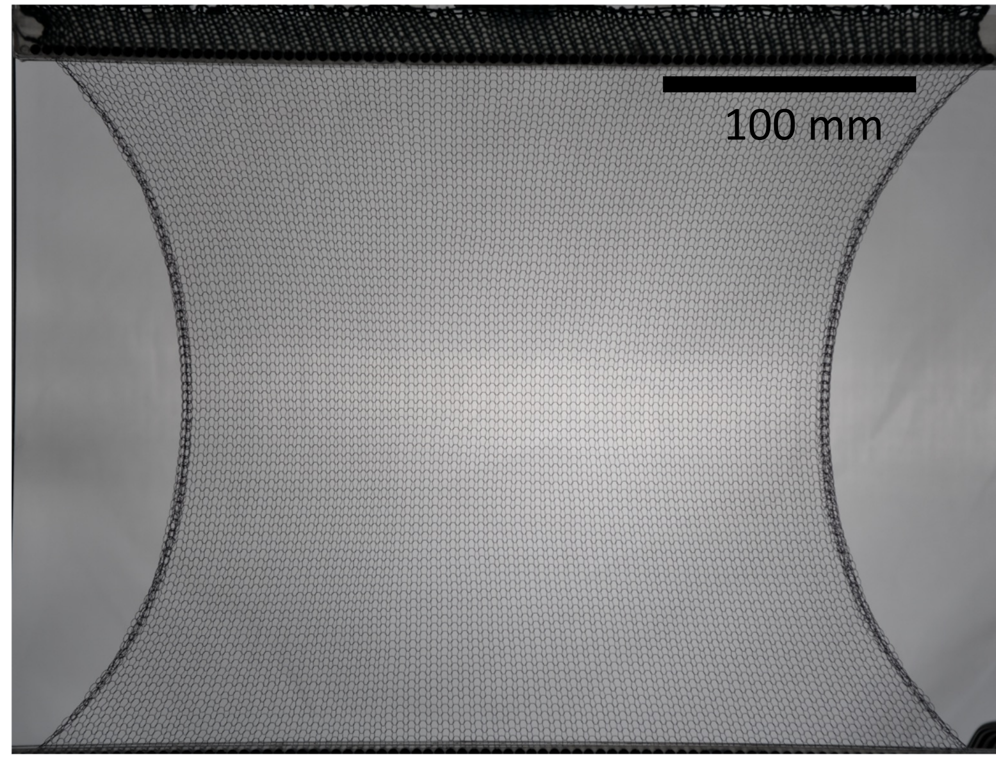
The Knit



Knitting machine Toyota KS858

Knit : overall size 83x83 stitches

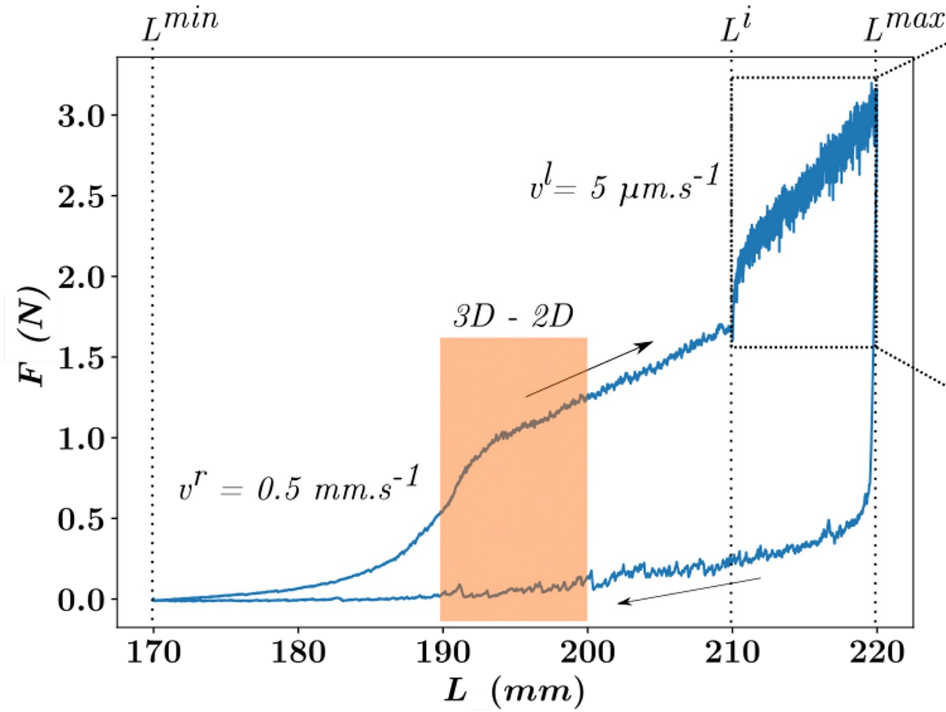
Yarn of 80 µm diameter

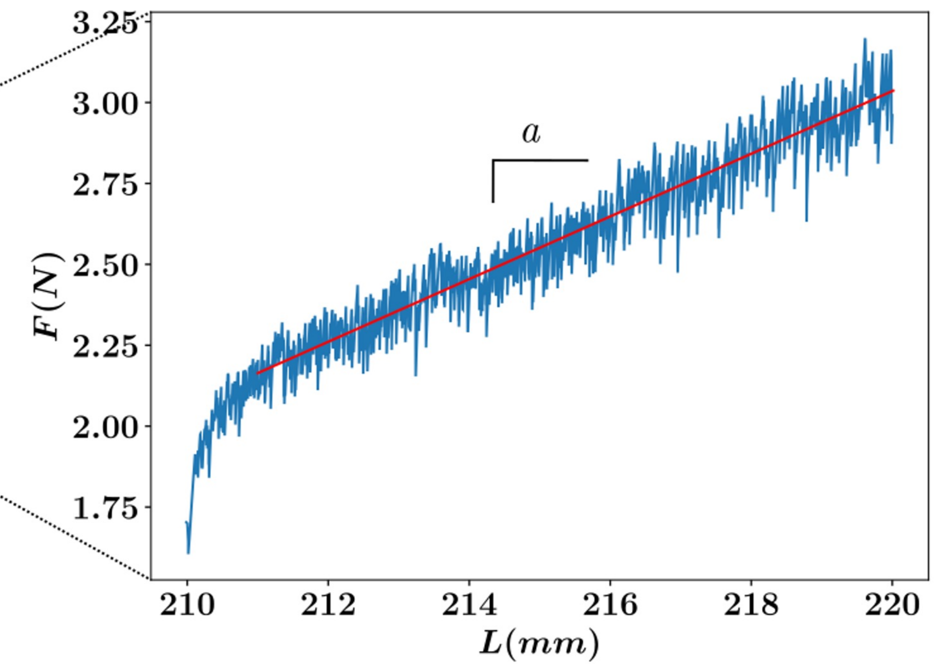


20 home-made knits

Force Drop Signal

Mechanical response of the fabric





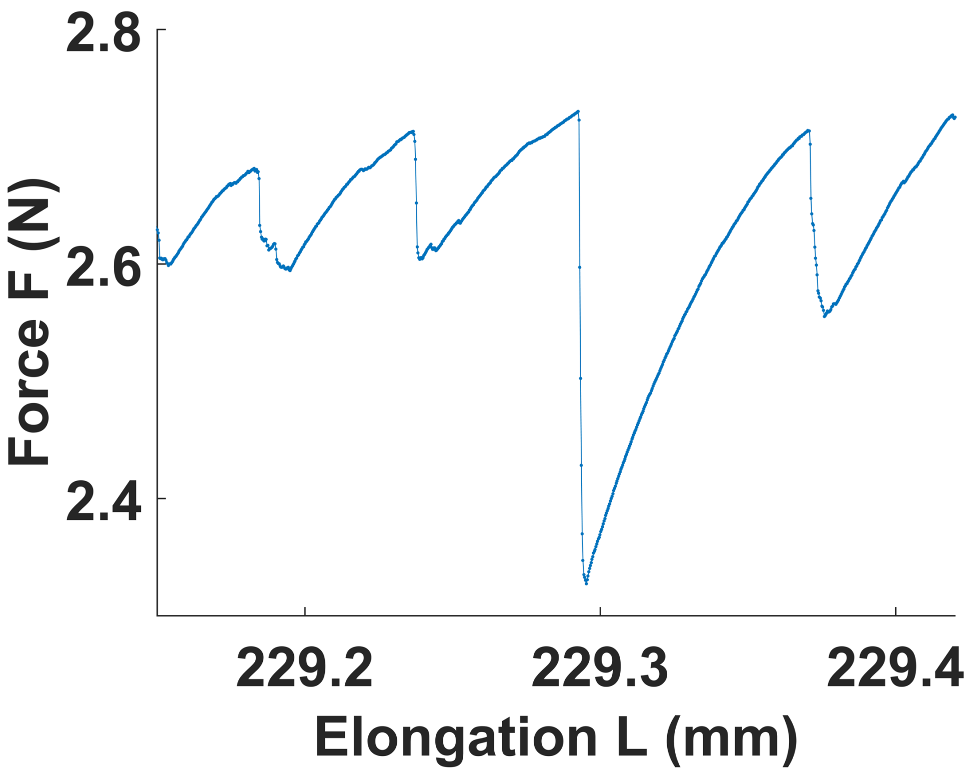
Affine elastic response: $\overline{F}(L) = b + aL$

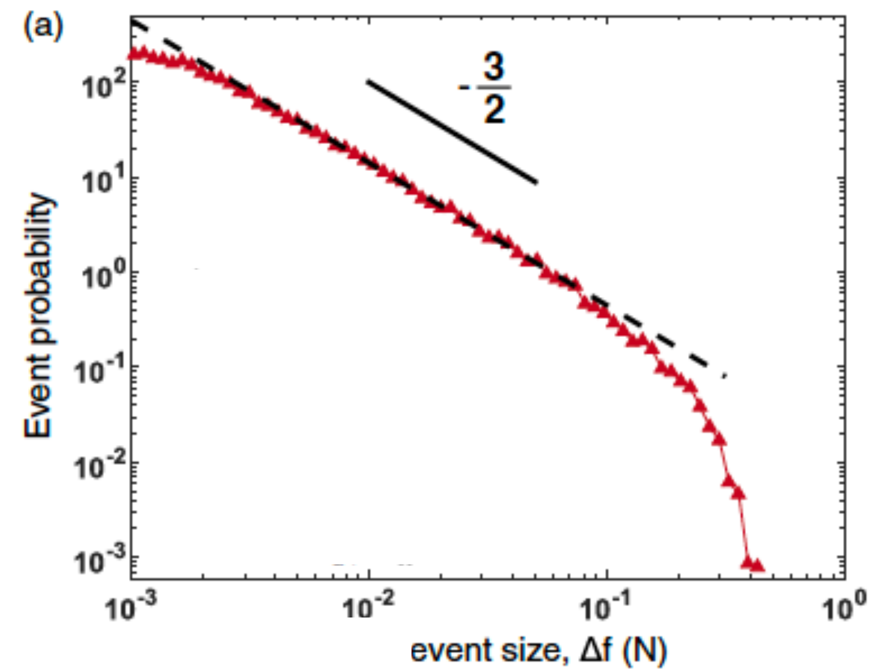
Fluctuations: $f(L) = F(L) - \overline{F}(L)$

22 experiments of 24h :

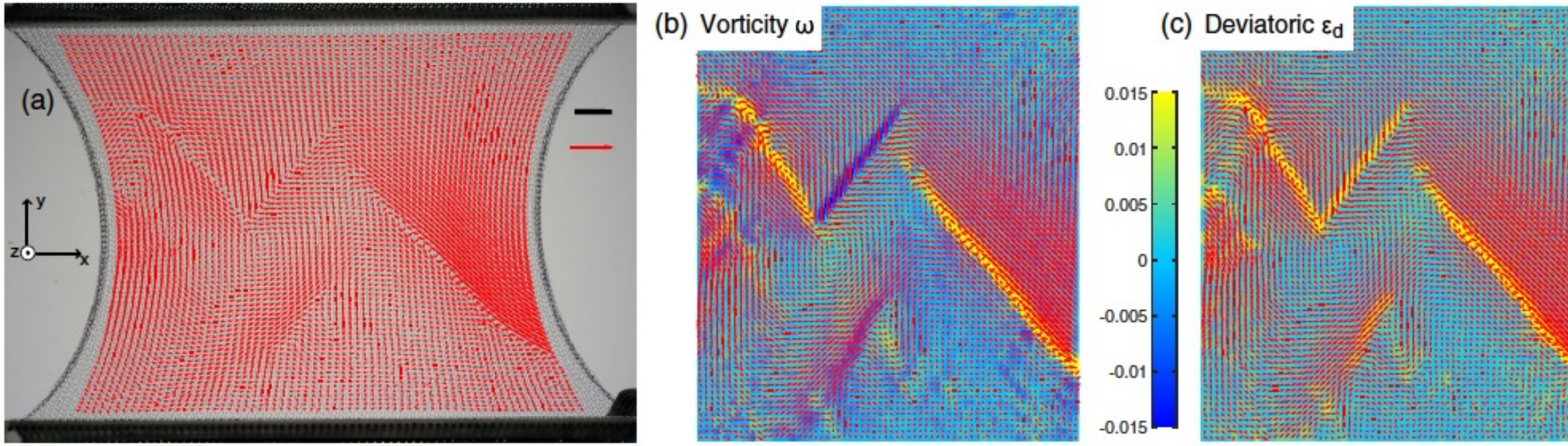
640 force fluctuation sequences & 1TB of pictures

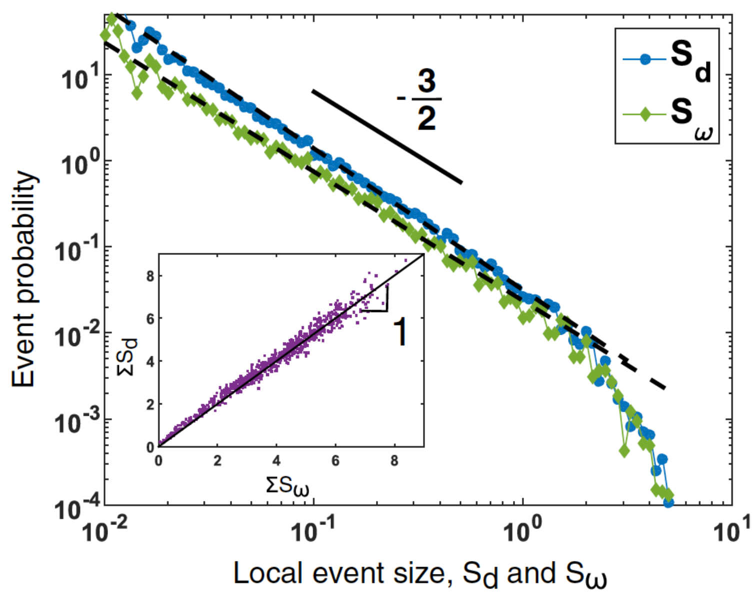
Knit slip

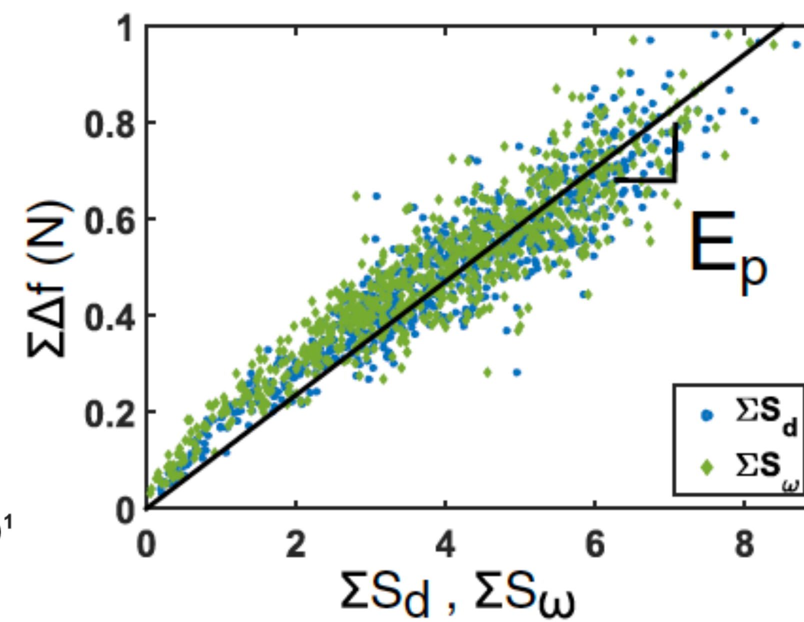

2.8
2.6
2.4
Force F (N)
229.2
229.3
229.4
Elongation L (mm)


(a)
- 3/2
Event probability
event size, Δf (N)

Spatial characterization : « faults »

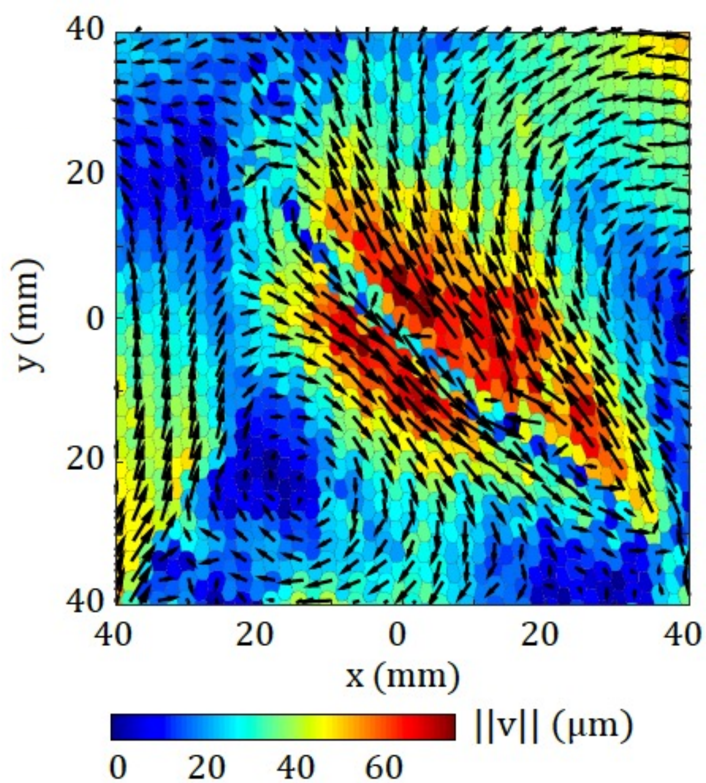


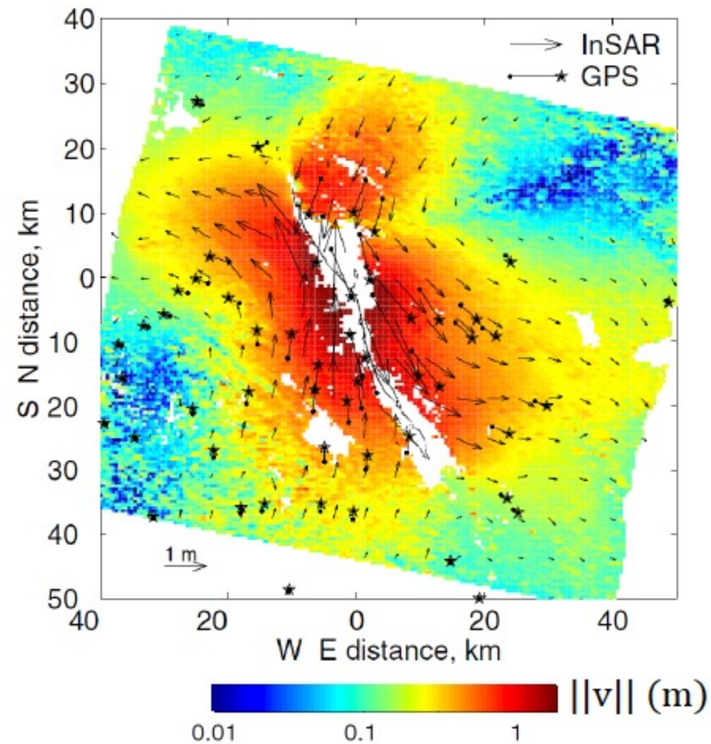




Faults : seismicity ?

- Morphology

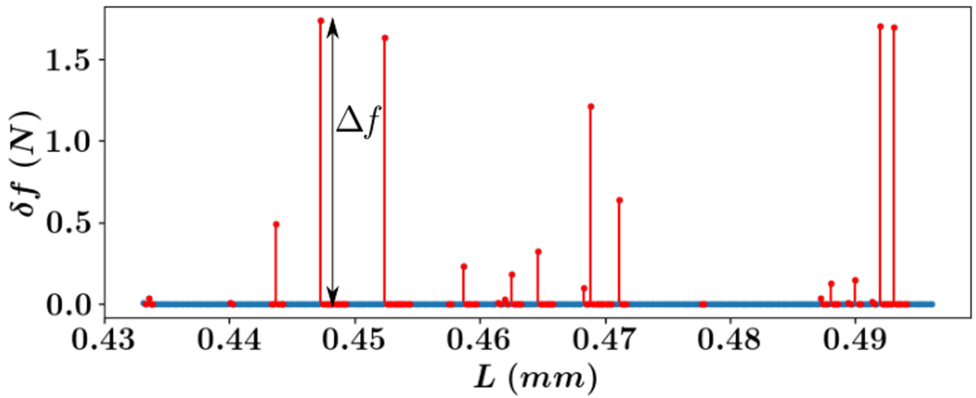




How to predict Amplitude ?

Events' amplitude signal

$$f(L) \longrightarrow \delta f(L) = \begin{cases} \Delta f & \text{if } L \text{ is the beginning of a drop} \\ 0 & \text{else.} \end{cases}$$

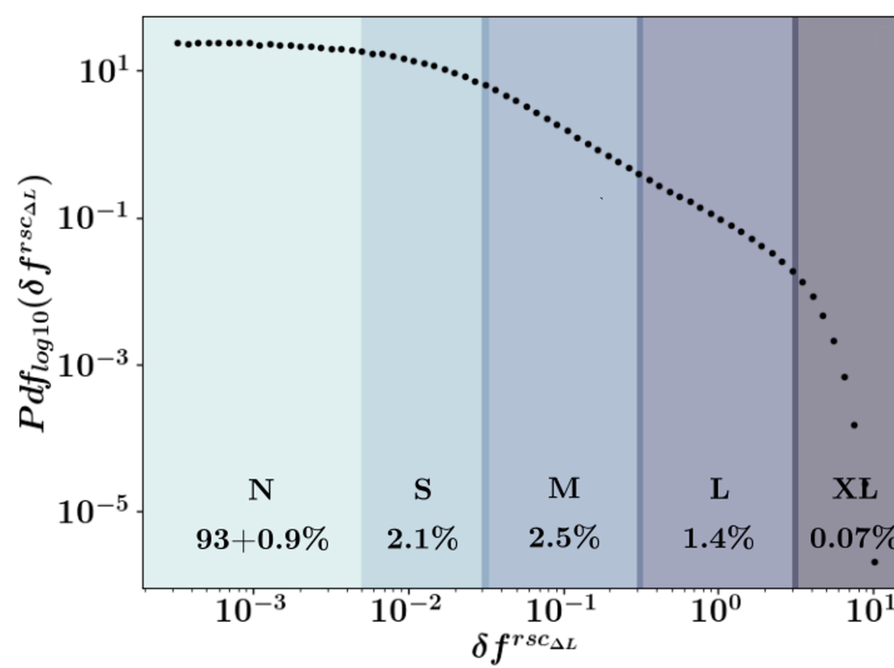


return time (pts)	Div. N	Div. S	Div. M	Div. L	Div. XL
$\delta f^{rsc_{\Delta L}}$	2 ± 1	47 ± 16	40 ± 55	69 ± 50	1352 ± 1534

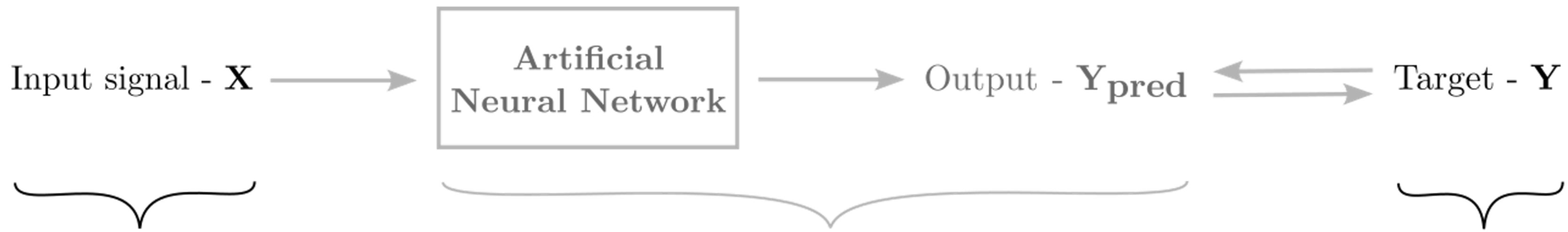
Non periodic & **Extremely rare** events

Distribution of events' amplitudes

Categories' proportion



Time Series Prediction of Future Events

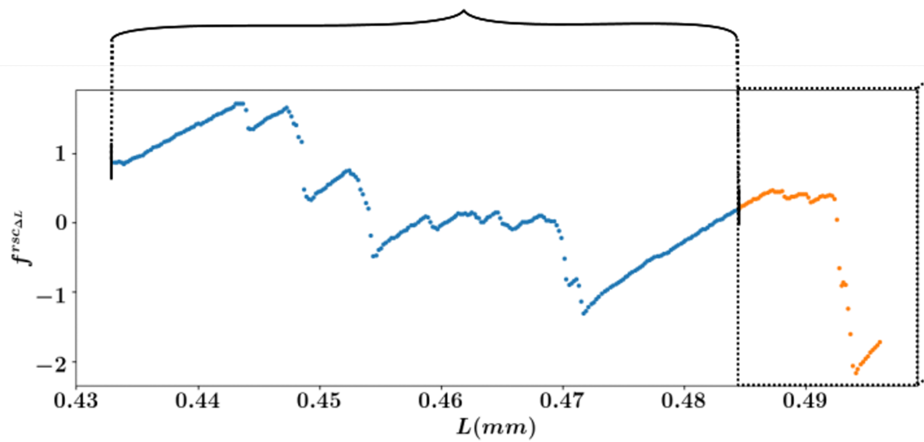


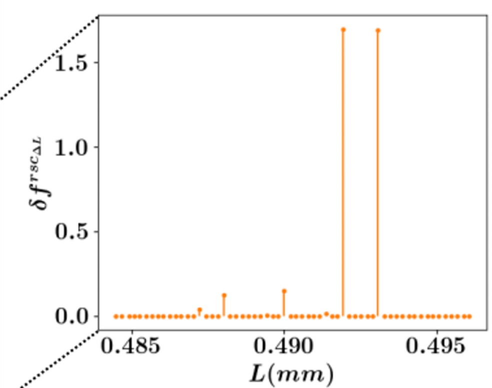
What do we **already** know ?

How to proceed ?

What do we **want to know** ?

Fluctuations time series





Next event amplitude

Extremly unbalanced

Y_{value}	Div. N	Div. S	Div. M	Div. L	Div. XL
$\delta f^{rsc_{\Delta L}}$	94%	2.1%	2.5%	1.4%	0.07%

$f_{size} = 256\ pts$

Time Series Prediction of Future Events

Input signal - **X** → Artificial Neural Network → Output - $\mathbf{Y_{pred}}$ ⇄ Target - **Y**

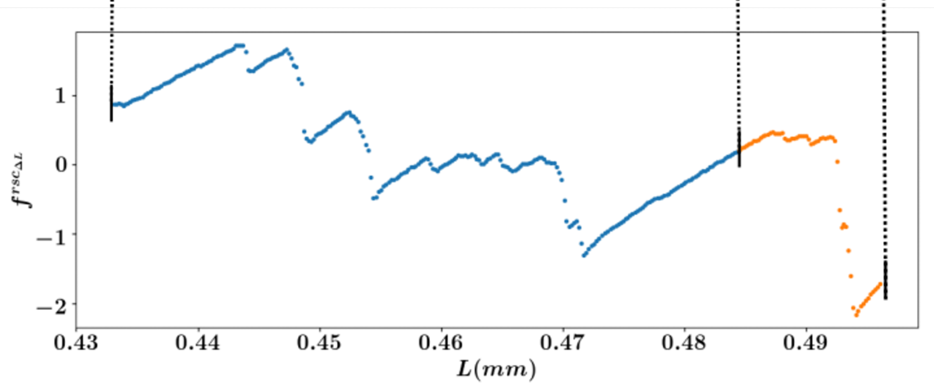
What do we **already** know ?

How to proceed ?

What do we **want to know** ?

Fluctuations time series

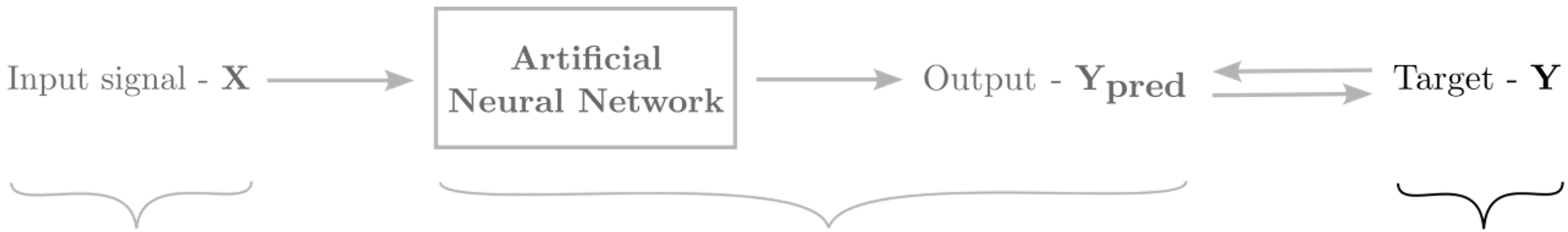
Horizon τ → Y_{value}



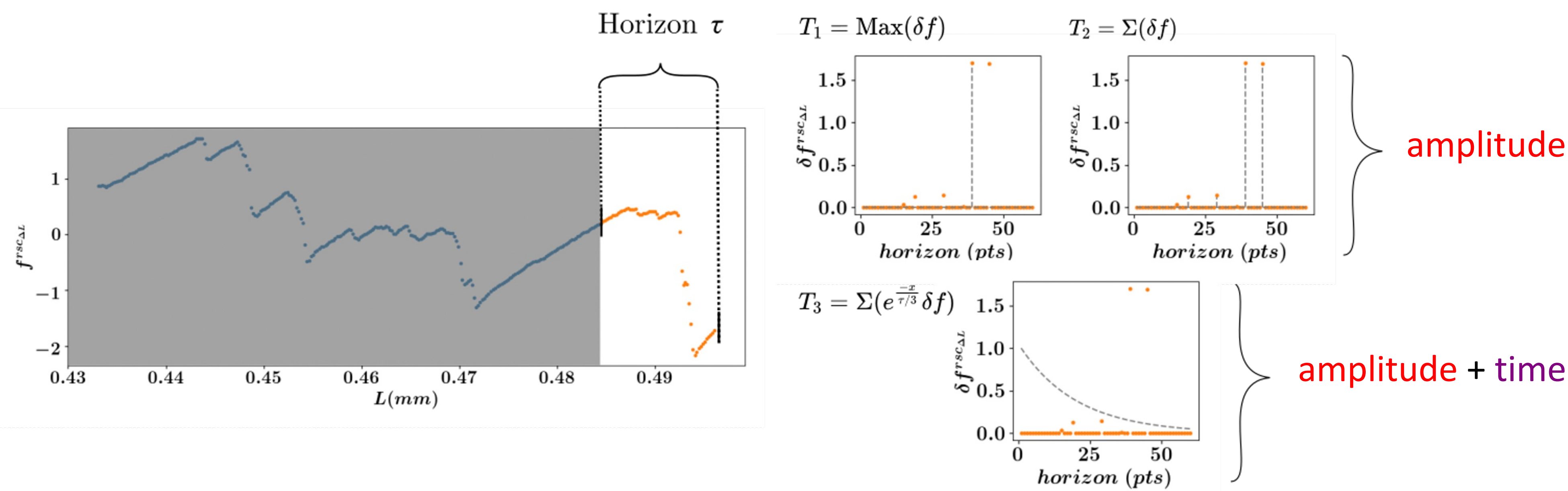
How to integrate
future amplitude signal information ?

$f_{size} = 256\ pts$ & $\tau = \{20,\ 40,\ 60\}\ pts$

Time Series Prediction of Future Events



What do we **already** know ? How to proceed ? What do we **want to know** ?



Future Events Classification

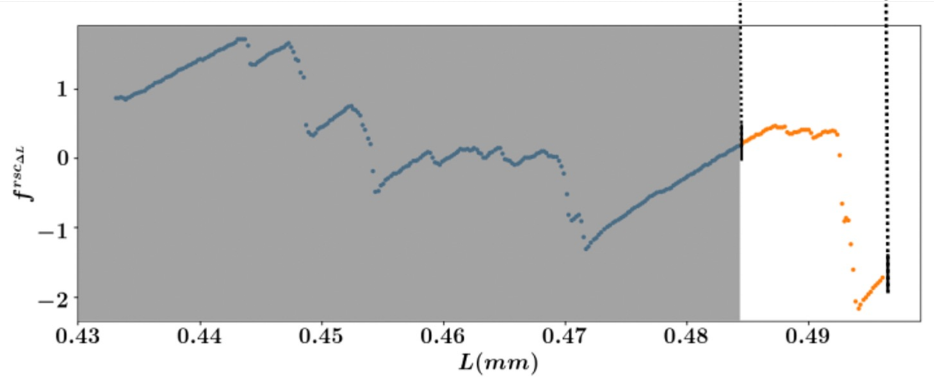
Input signal - $\mathbf{X}$ → Artificial Neural Network → Output - $\mathbf{Y_{pred}}$ ⇄ Target - $\mathbf{Y}$

What do we **already** know ?

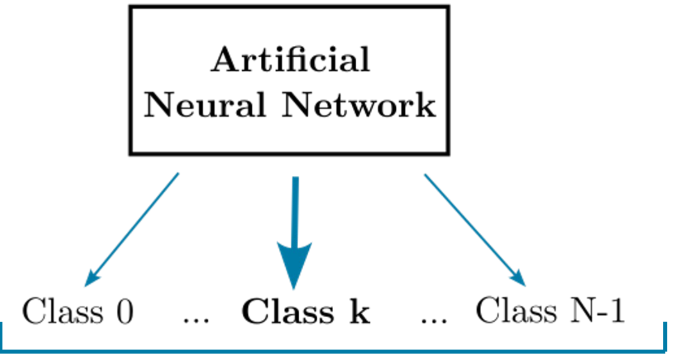
How to proceed ?

What do we **want to know** ?

Horizon τ ⟶ $Y_{value} = T_i(\tau, \delta f)$

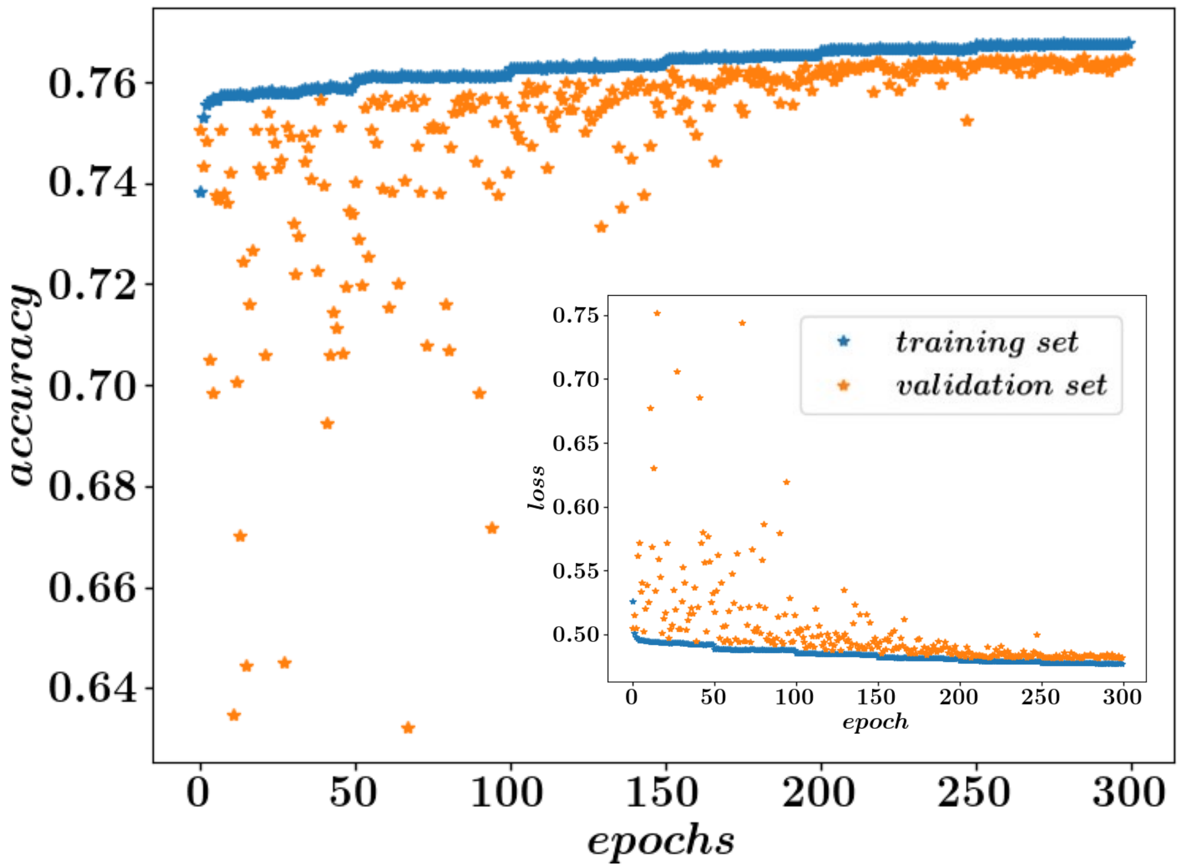


Classification such as $T_i(\tau, \delta f) \in Class\ k$



Arbitrary choices to make on N & thresholds

Training with Neural Network



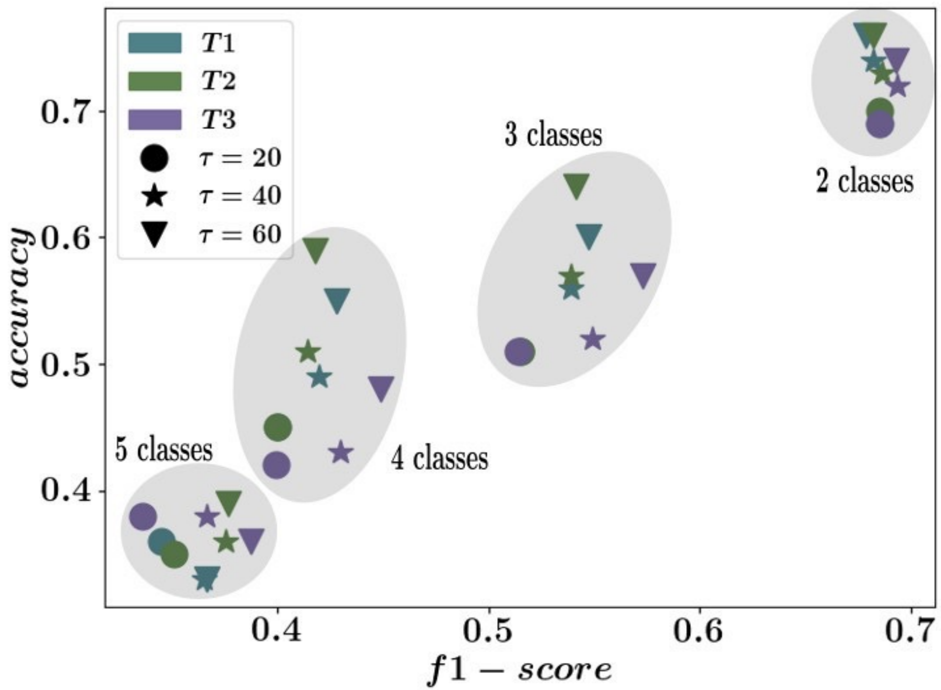
Architecture : ResNet18 1D
N equiprobable classes for learning

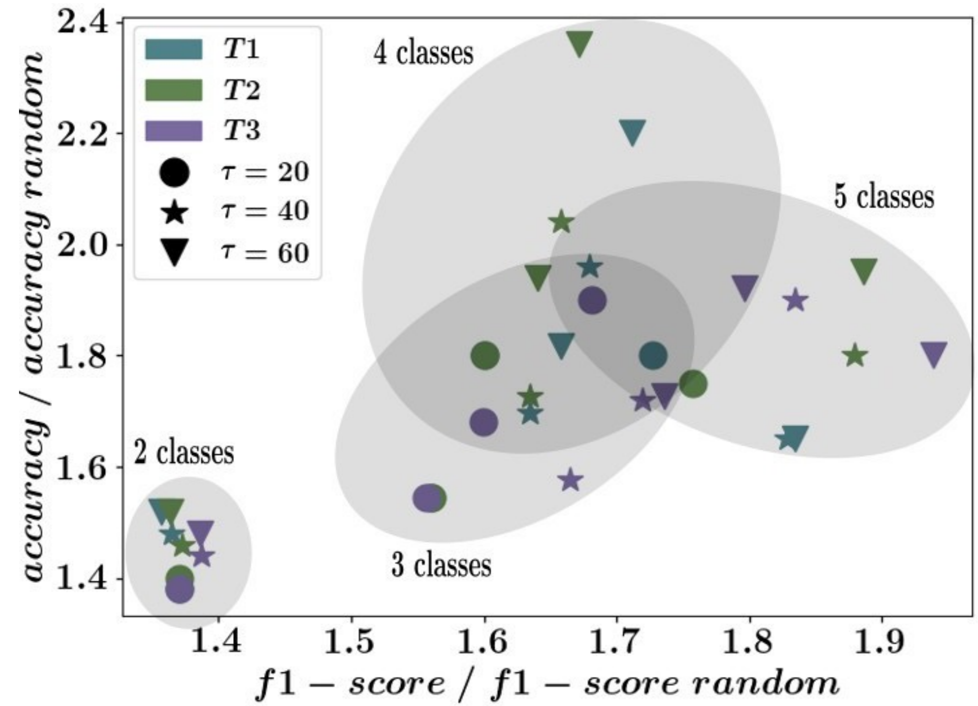
training on 1M sequences (over 21M)

validation on 200k sequences (over 2.8M)

test on 2.8M new sequences

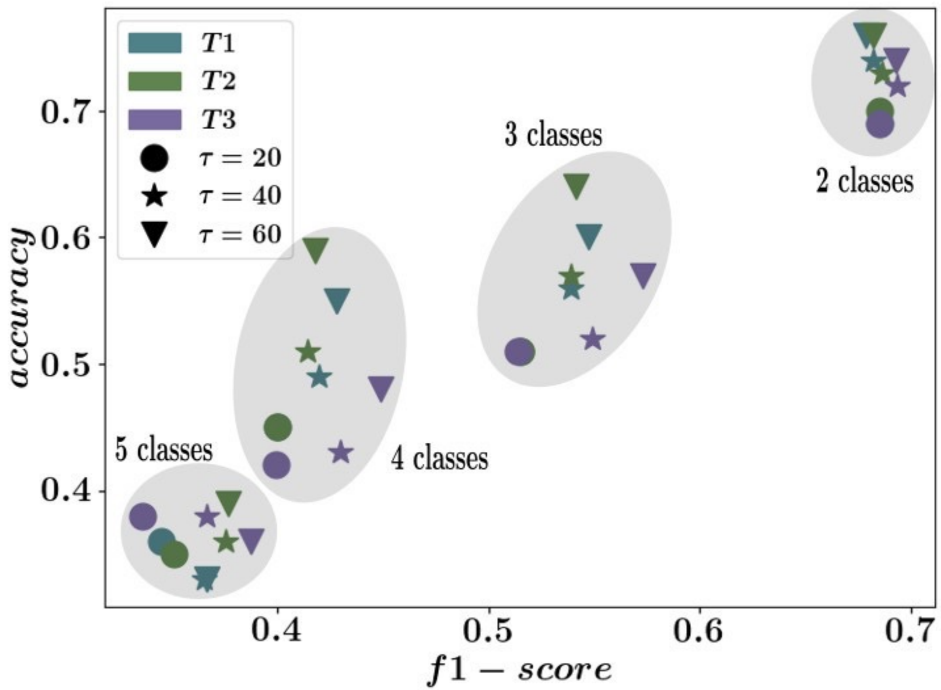
Standard Metrics for Evaluation

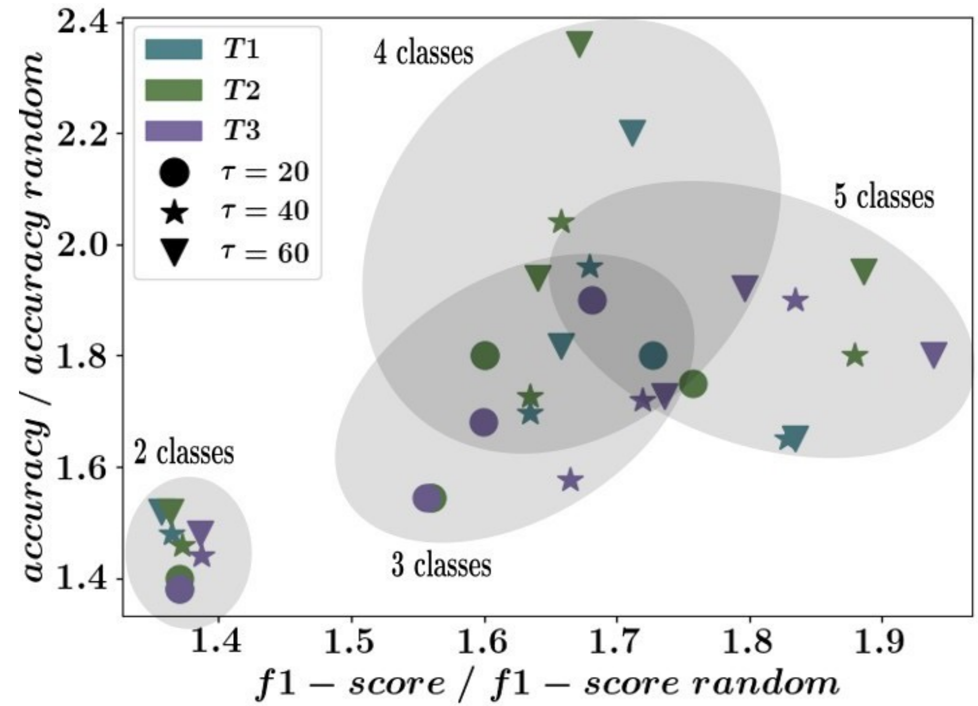




Learning with respect to **random** choice

Standard Metrics for Evaluation





How compare models ?
How define Best Model ?

Learning with respect to **random** choice

Département de Physique
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PR[AI]RIE
PaRis Artificial Intelligence Research InstitutE
cnrs

KnitCity : Game Theory

EA, Maxis Studio

Goal :

Evacuate people before deadly events (big/very big).

Possible decision at each step :

- stay in city
- evacuate city

Seismic Risk Policy Design

How relate a **prediction** on a target with a **decision making** ?

Predictor From Neural Net

+

=

Human Cost

+

=

Social Cost

Naive Policy & Reinforcement Leanring

Predictor == Danger

N last predictors

Policy

learning

Reward = - Social Cost - μ Human Cost

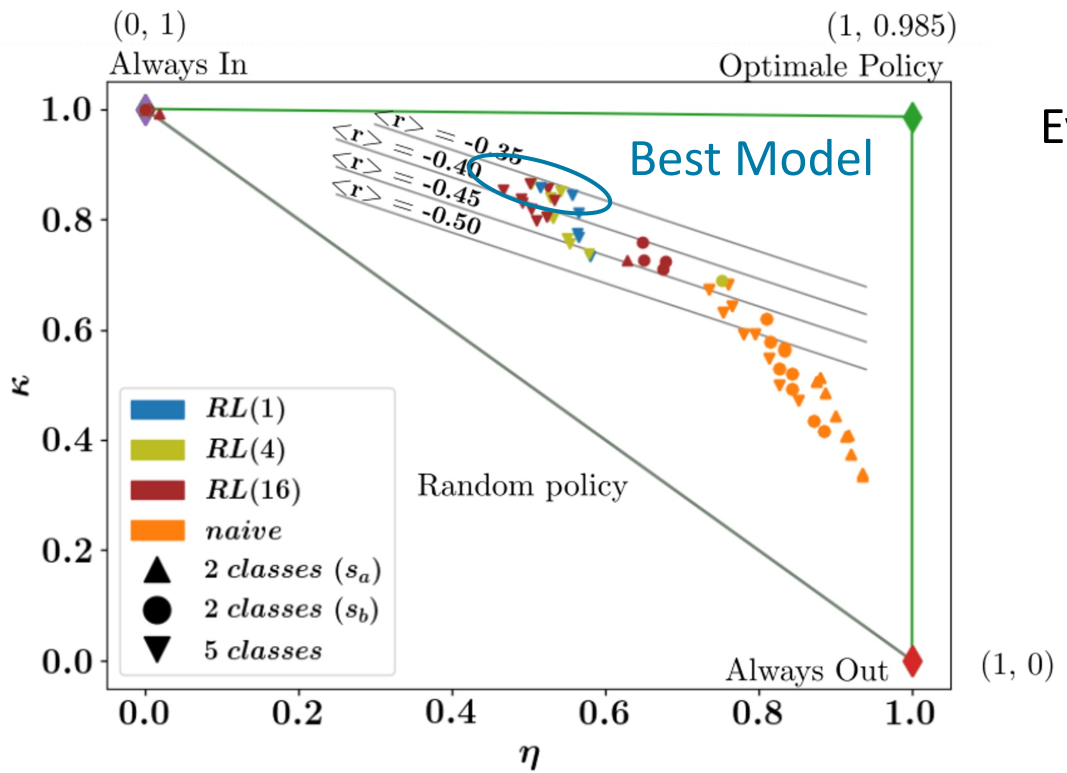
Evaluation Space

κ ~ proportion of non evacuated days

η ~ proportion of saved people

$<r> = <c_h + c_s>$

- **single, reliable, well-defined** metric
- with respect to **seismic risk**



Evaluate & compare: 1. Predictive model
2. Decision-maker

1. Predictive model
- N=5 > N=2
- T3 > T1 & T2
- τ = 20 > τ = {1, 40, 60}

2. Decision-maker:

RL(n) > naive

with respect to <r>

Optimal nb of predictions

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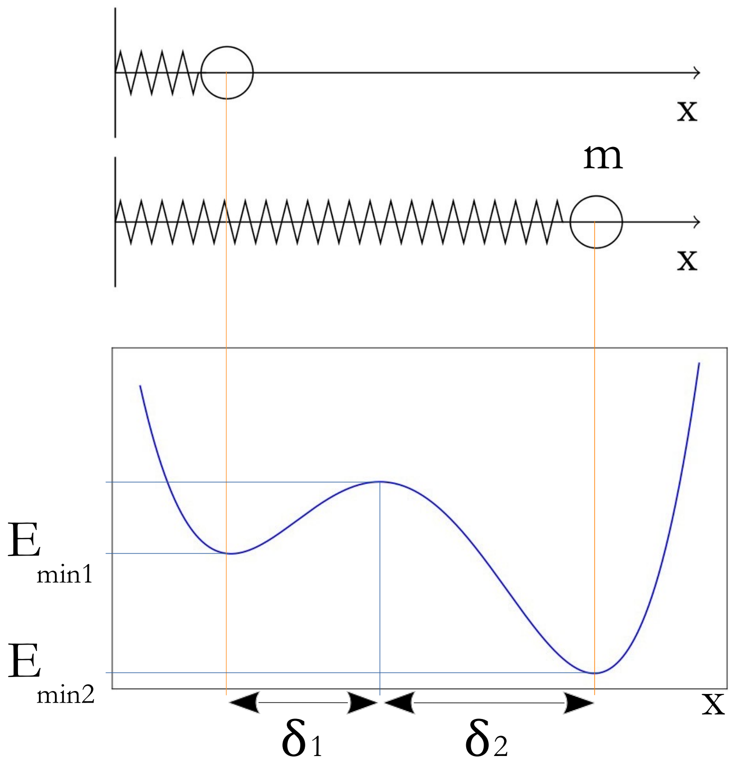
Mechanical memory manipulation using Reinforcement Learning

Laura Michel

Théo Jules - Frédéric Lechenault

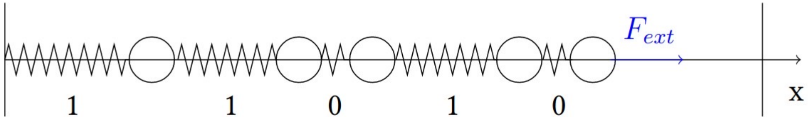
Controlling a chain of bistable springs



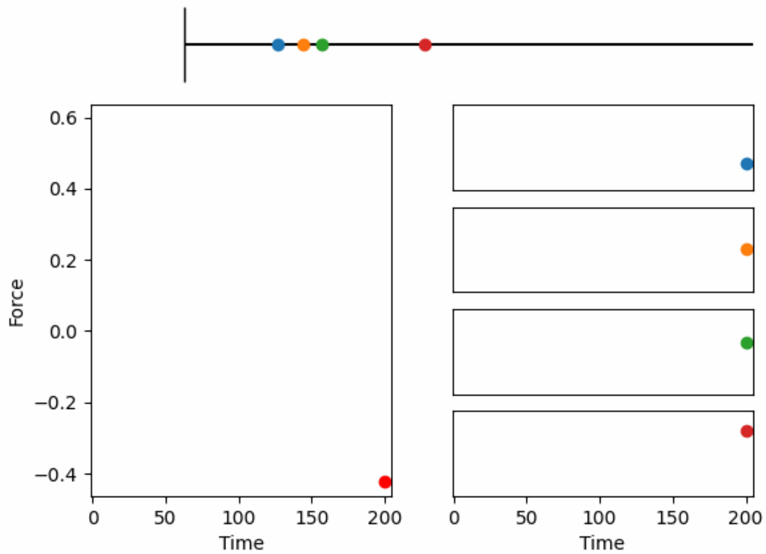
Fundamental block of the mechanical memory system – bistable spring-mass system.

Simulation of the multistable system

- Coupled bistable spring-mass systems :



11010



- Mechanical response of each block :

$$F(x) = -kx(x-\delta_1)(x-\delta_2)$$

- Friction coefficient c_f

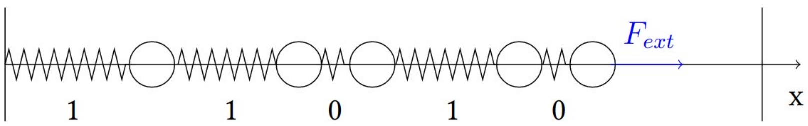
- Numerical simulation of the system – resolution via RK4

x

- **How to control the external force to bring the system to a given state ?**

Simulation of the multistable system

- Coupled bistable spring-mass systems :



11010

- Mechanical response of each block :

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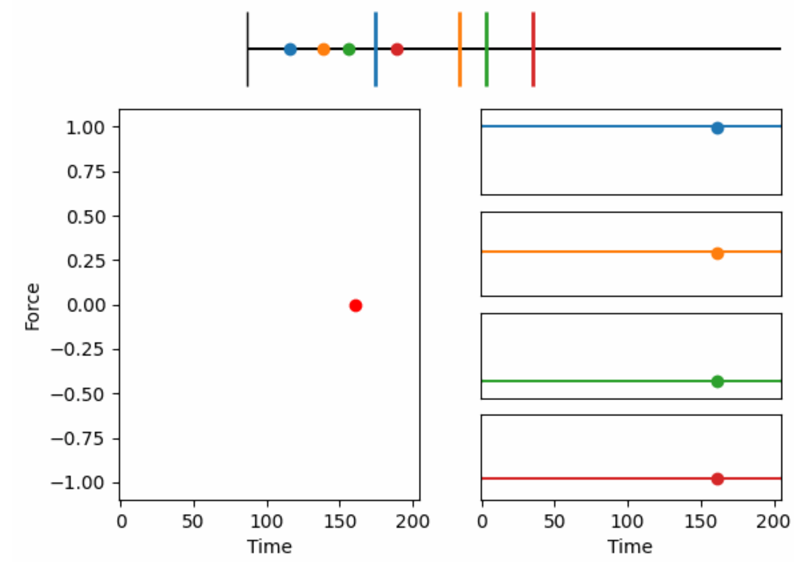
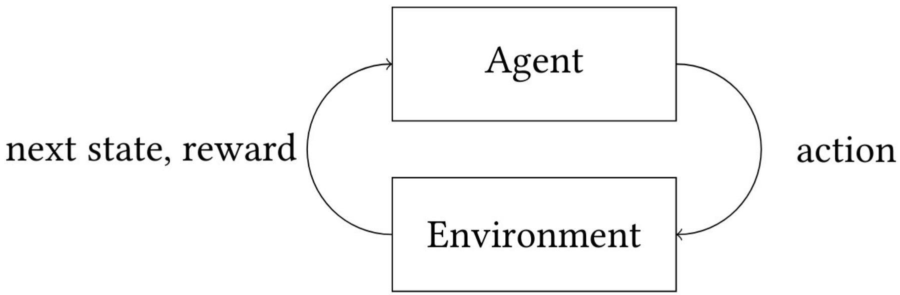
x



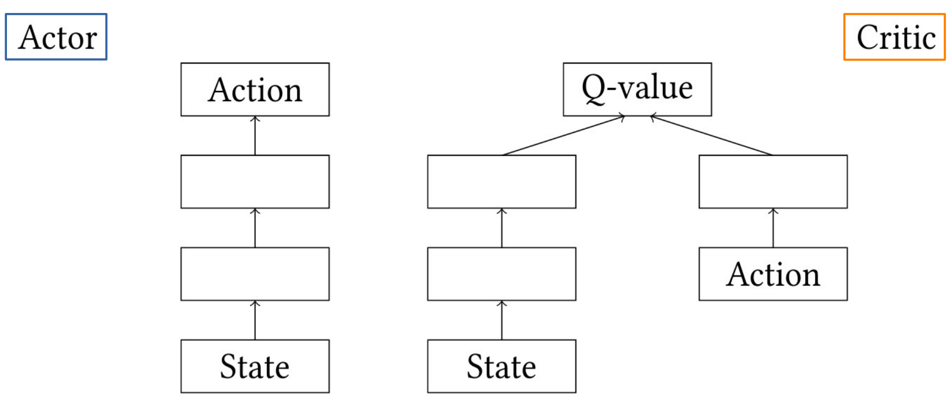
- **How to control the external force to bring the system to a given state ?**

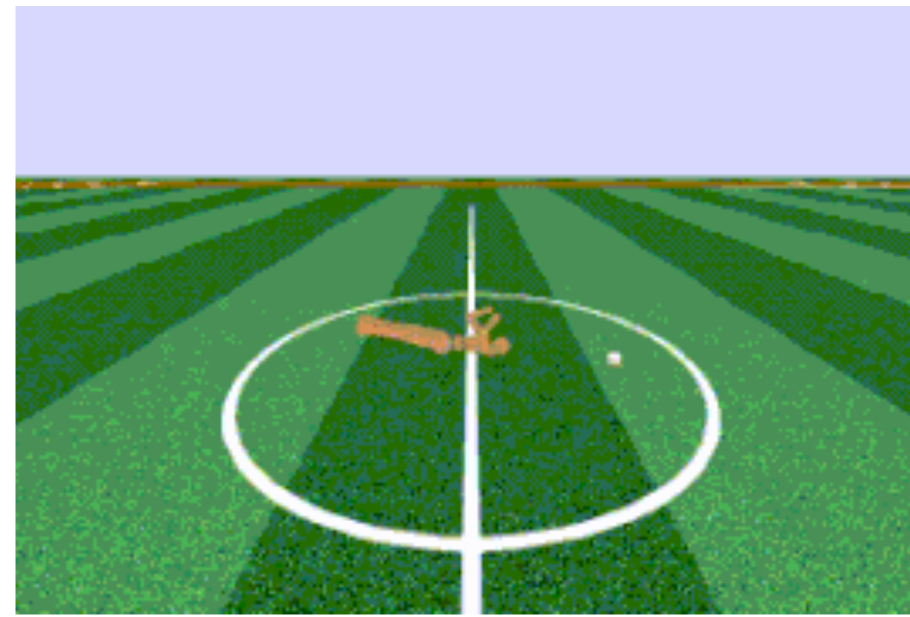
Reinforcement Learning

- RL principle



- Deep Deterministic Policy Gradient



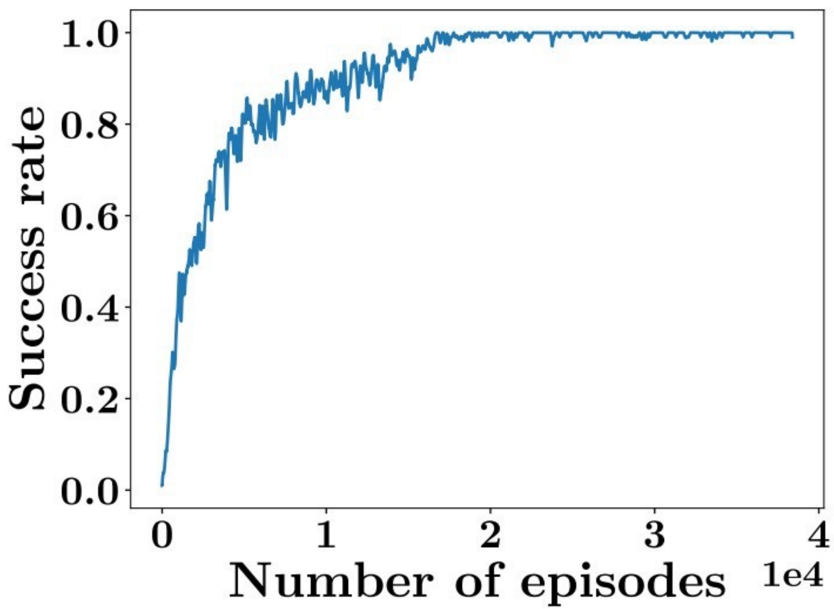


OpenAI

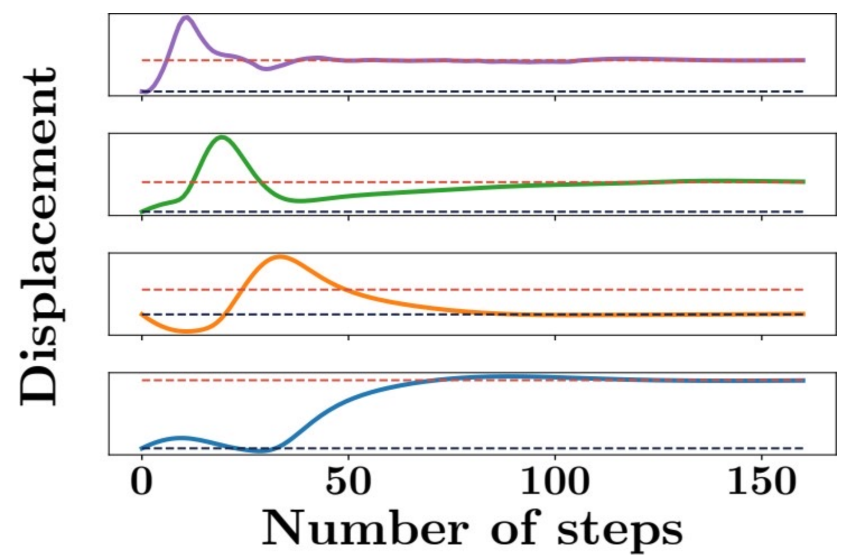
Convergence

- **Proof of concept** – four springs system : 2^4 target states.

Learning phase

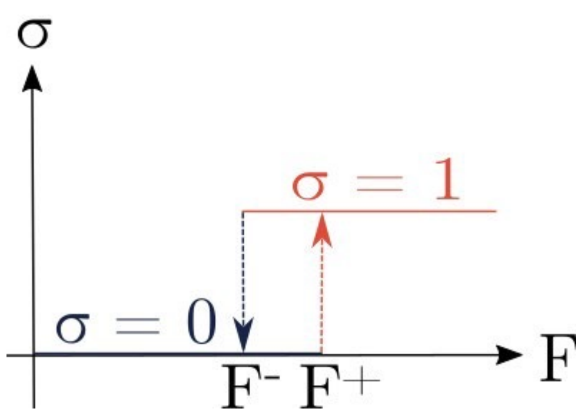


Test phase – 0000 → 1011

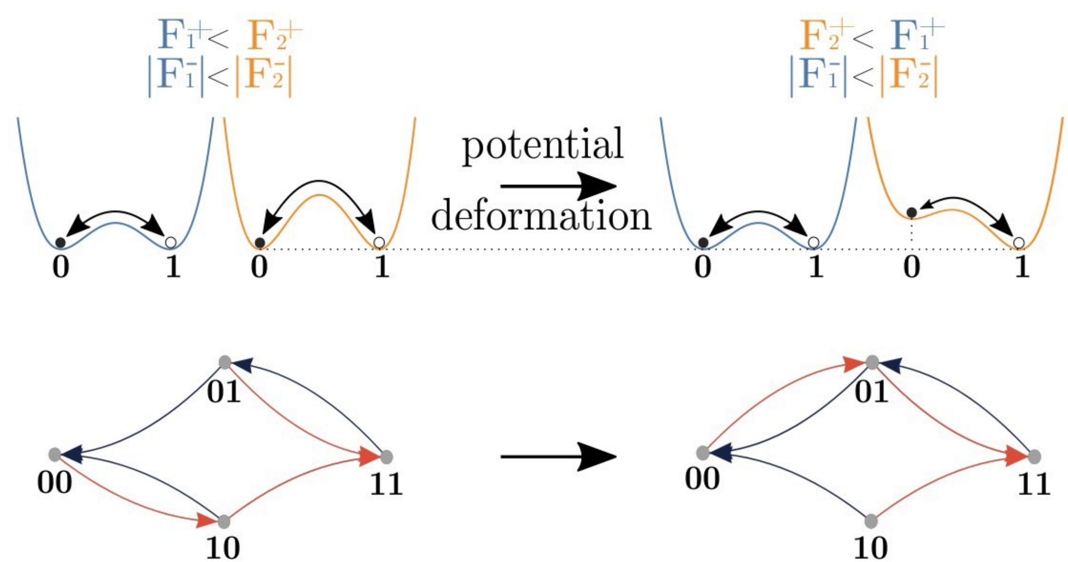


Garden of Eden states

- **Disorder chosen to possess GoE states** – example with two springs



Transition cycle of an hysteron

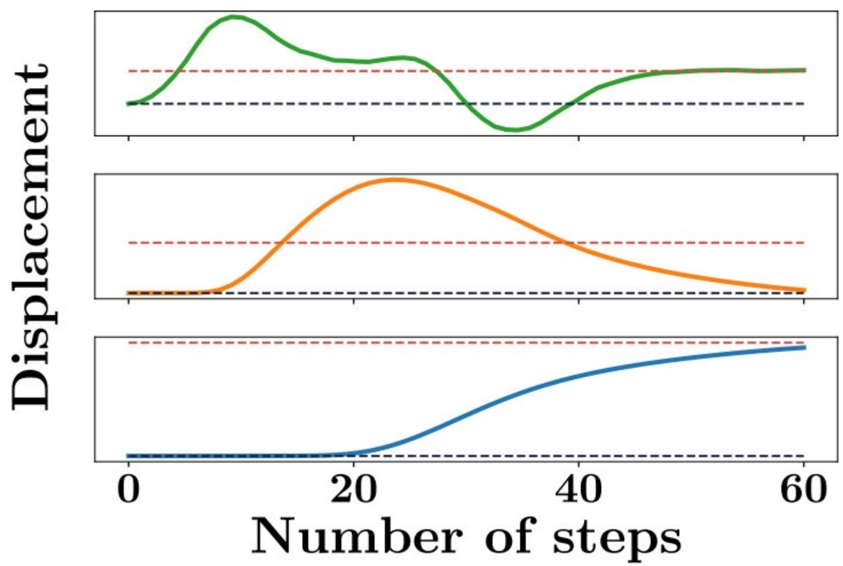


Two different disorders. Left : no GoE state. Right : one GoE state 10.

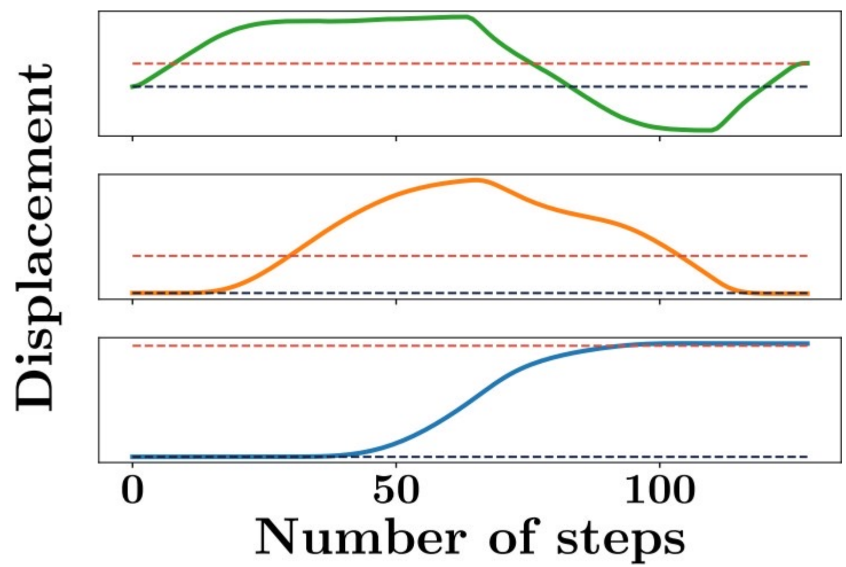
Reaching GoE states dynamically

- **Example with three springs** – Reaching the GoE 101 from the state 000

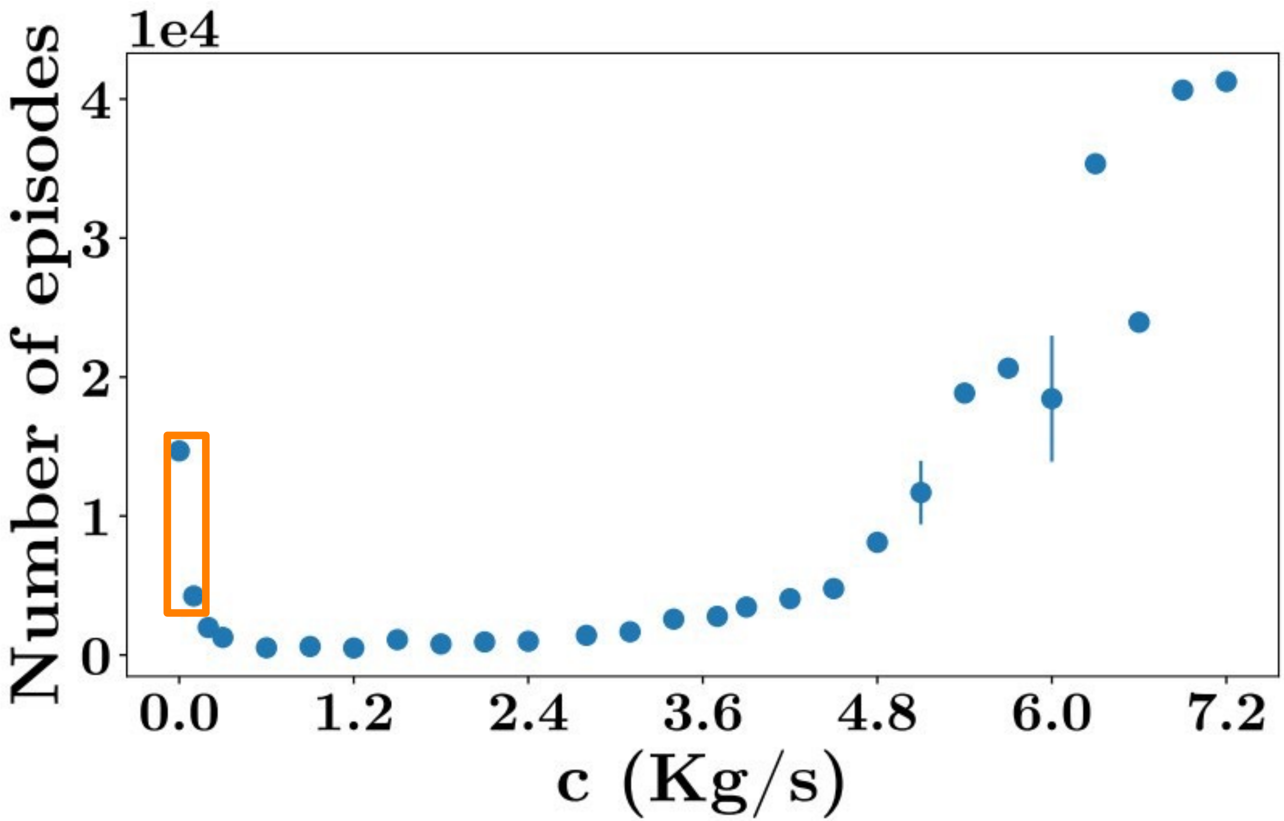
Low dissipation



Overdamped regime

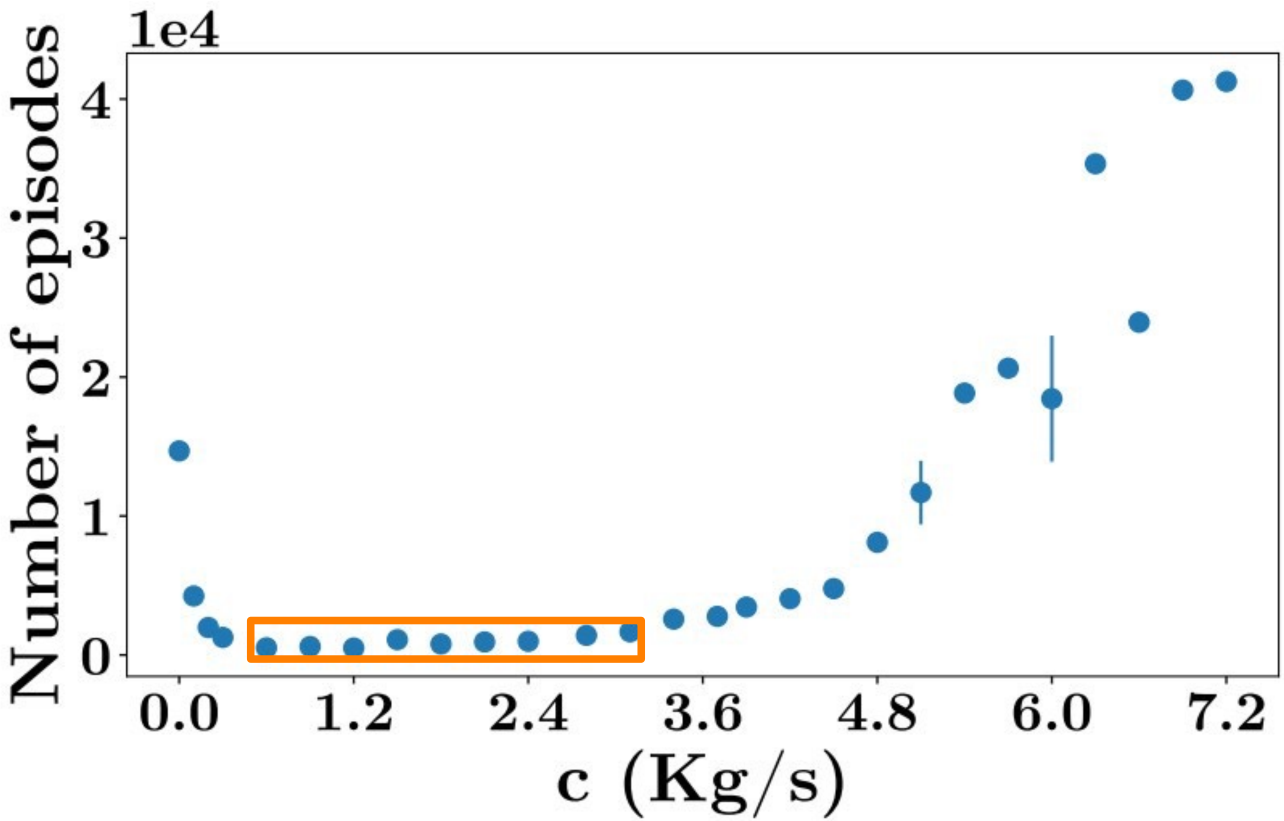


Physical limits of the system



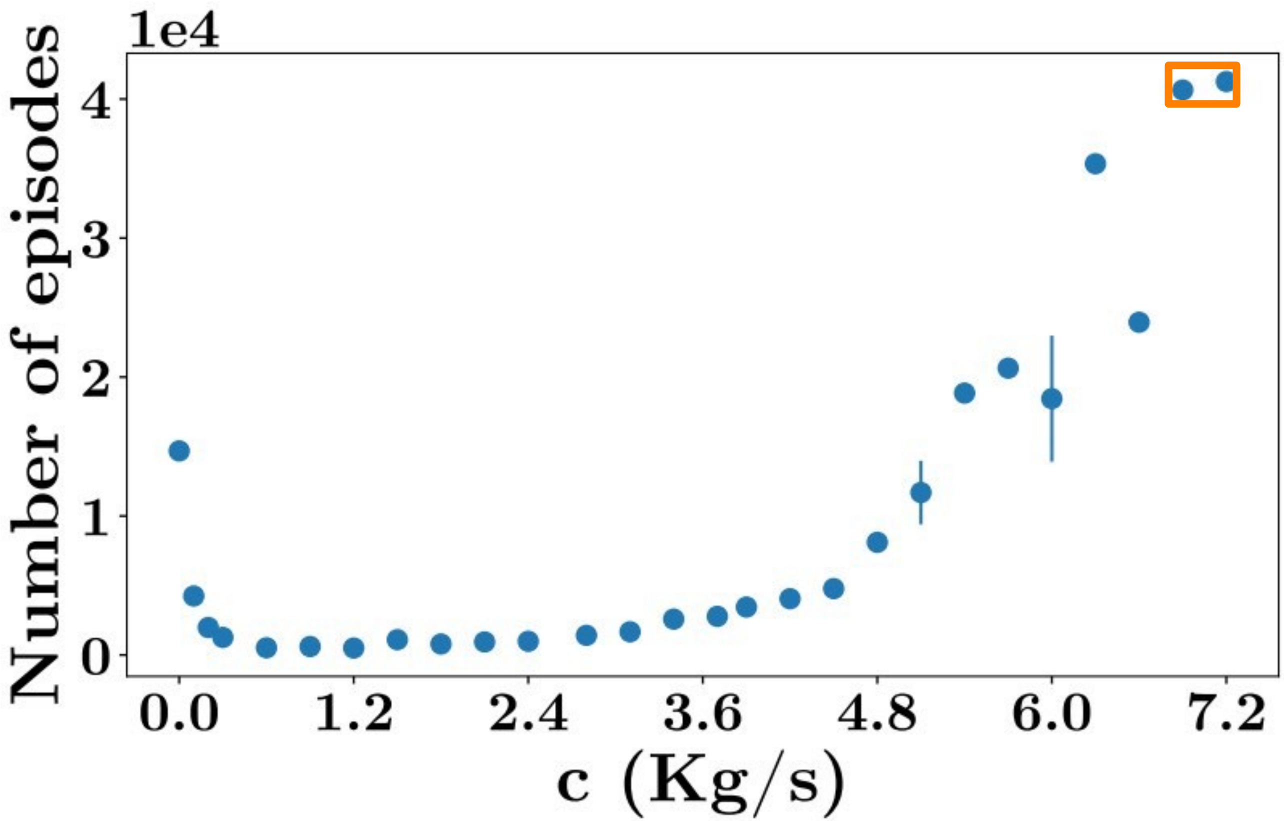
Learning becomes difficult for c ~ 0 Kg/s.

Physical limits of the system



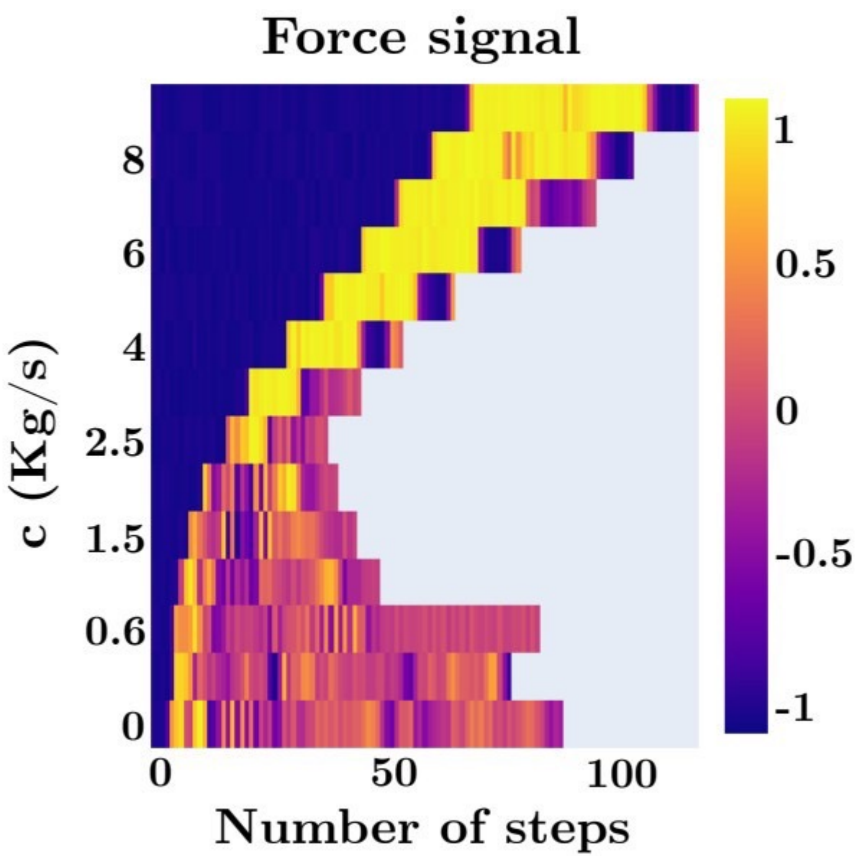
Minimum for 0.3<c<3 Kg/s.

Physical limits of the system



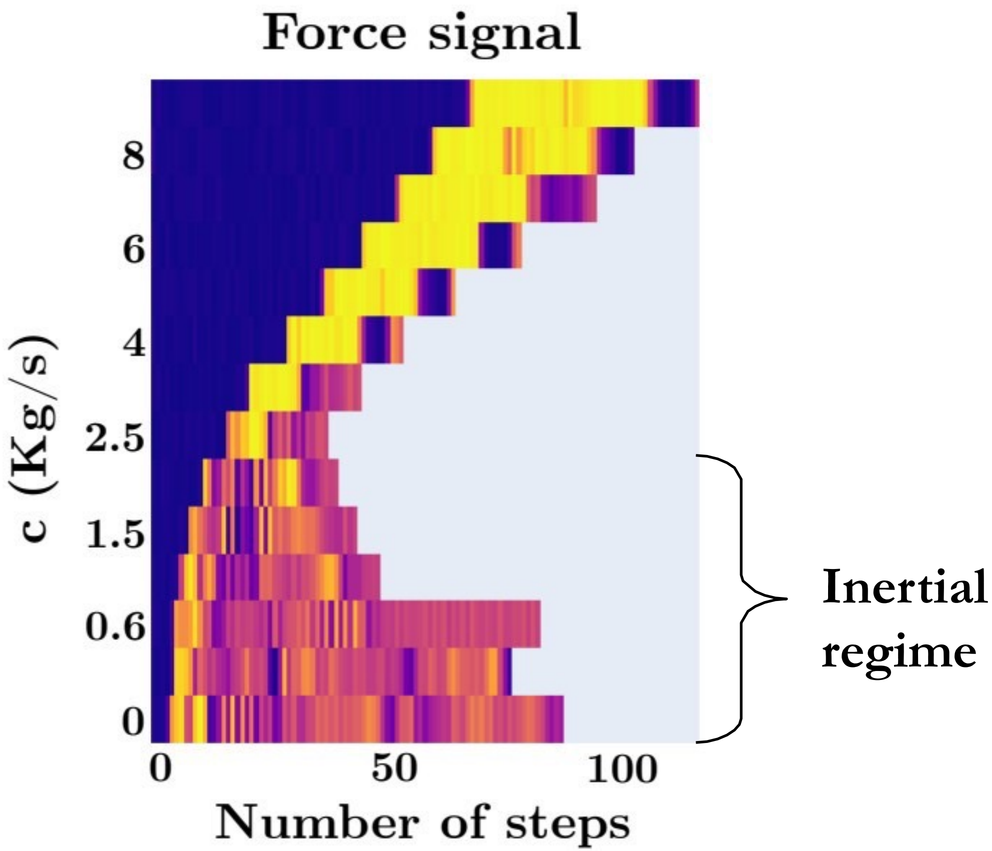
Divergence for c>7 Kg/s.

Two internal time scales

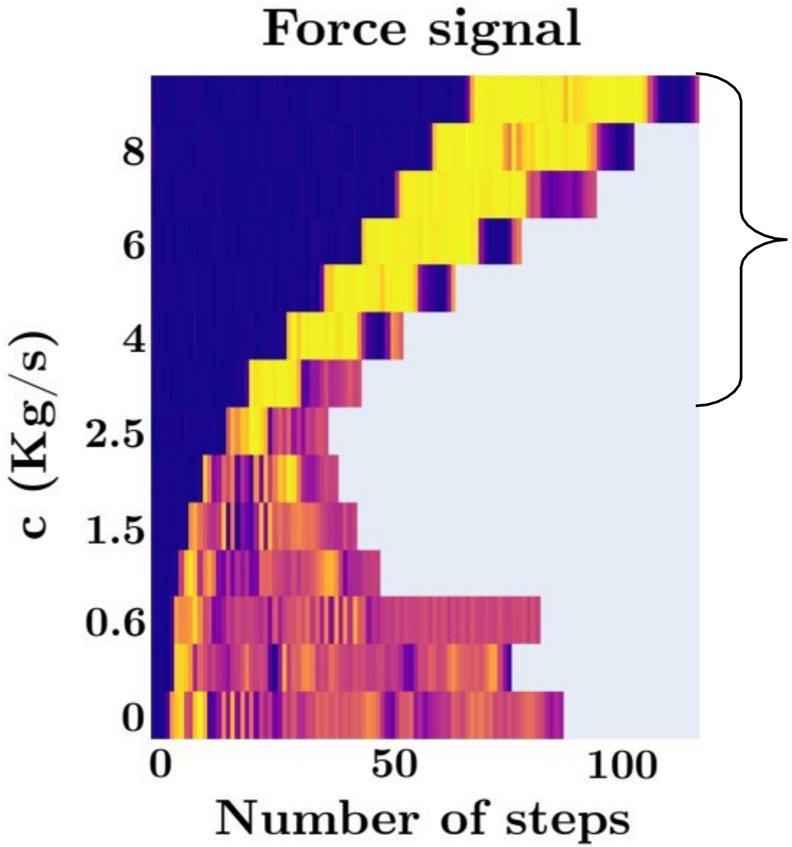


- **Continuous actions –**
  Force signal ϵ [-Fmax, Fmax], Fmax = 1 N

Two internal time scales

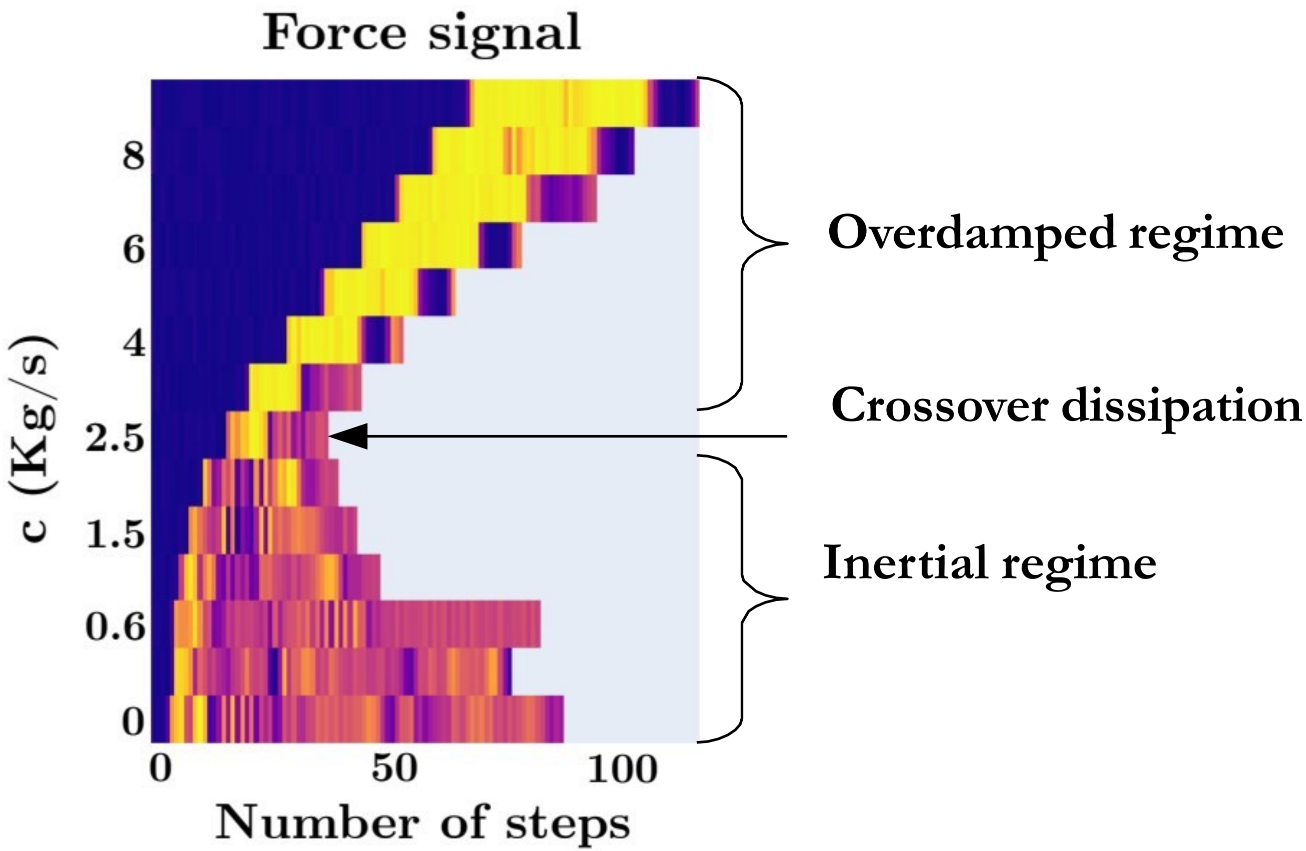


Two internal time scales

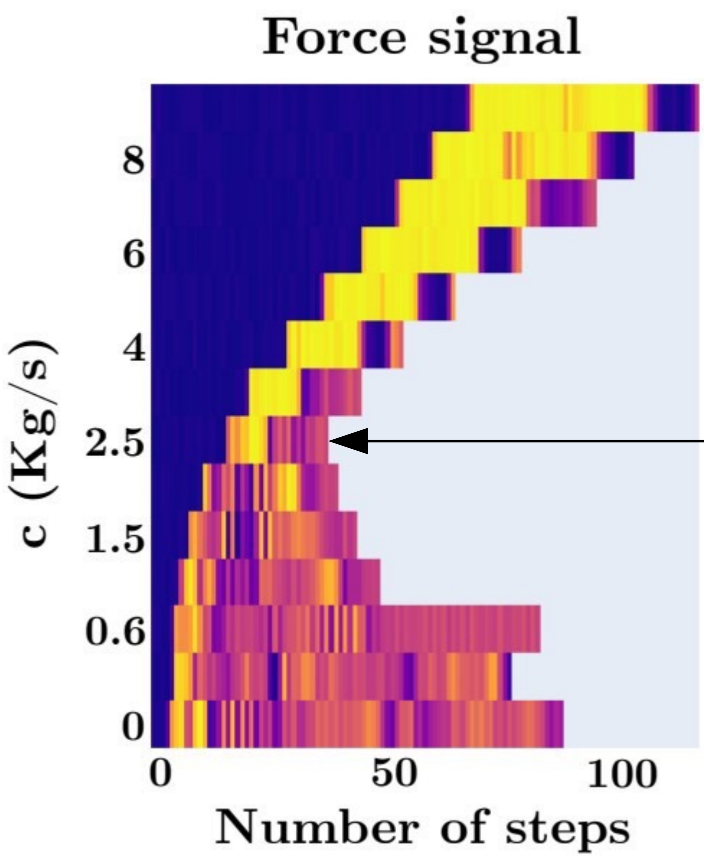


Overdamped regime

Two internal time scales



Two internal time scales



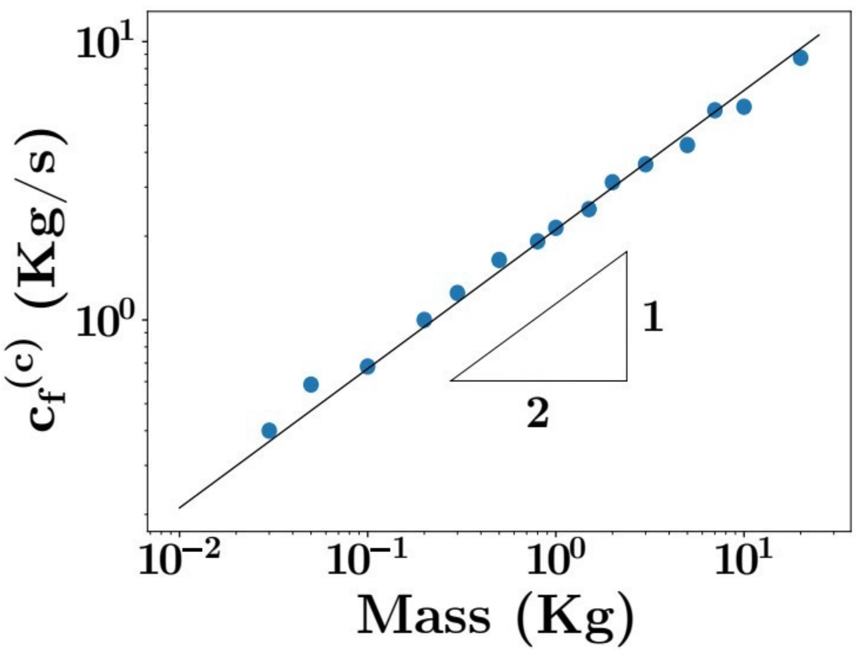
τ : typical time at which **inertia** becomes **negligible** $\propto$ **1/c**

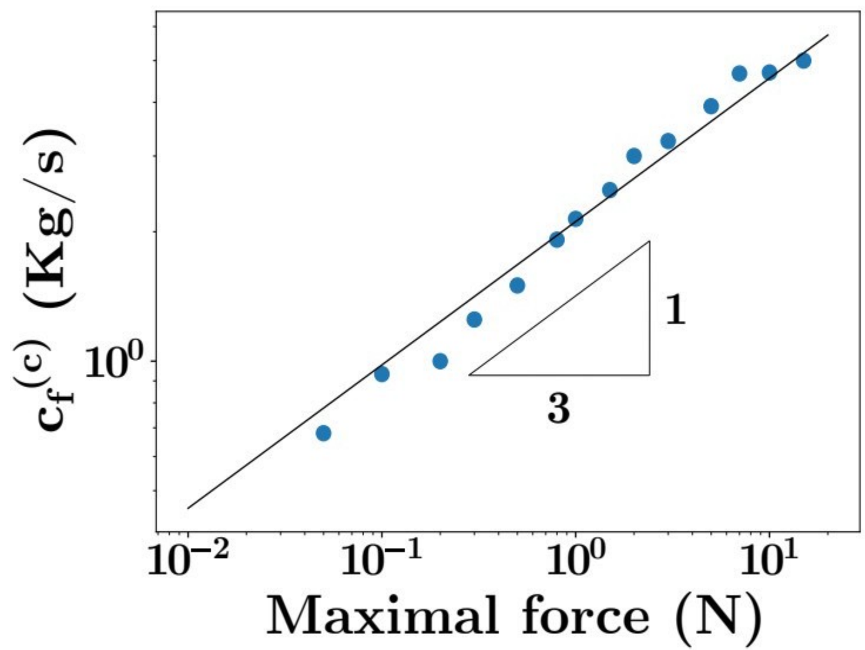
t_c : typical time at which **forcing propagates** in neighboring springs $\propto$ **c**

Crossover dissipation for $\tau = t_c$

Crossover dissipation

- **Theoretical crossover dissipation :** $c_f^{(c)} \sim m^{1/2} k^{1/6} F_{\max}^{1/3}$





This afternoon ?