How Machine Learning can help in earthquake control and fault mechanics

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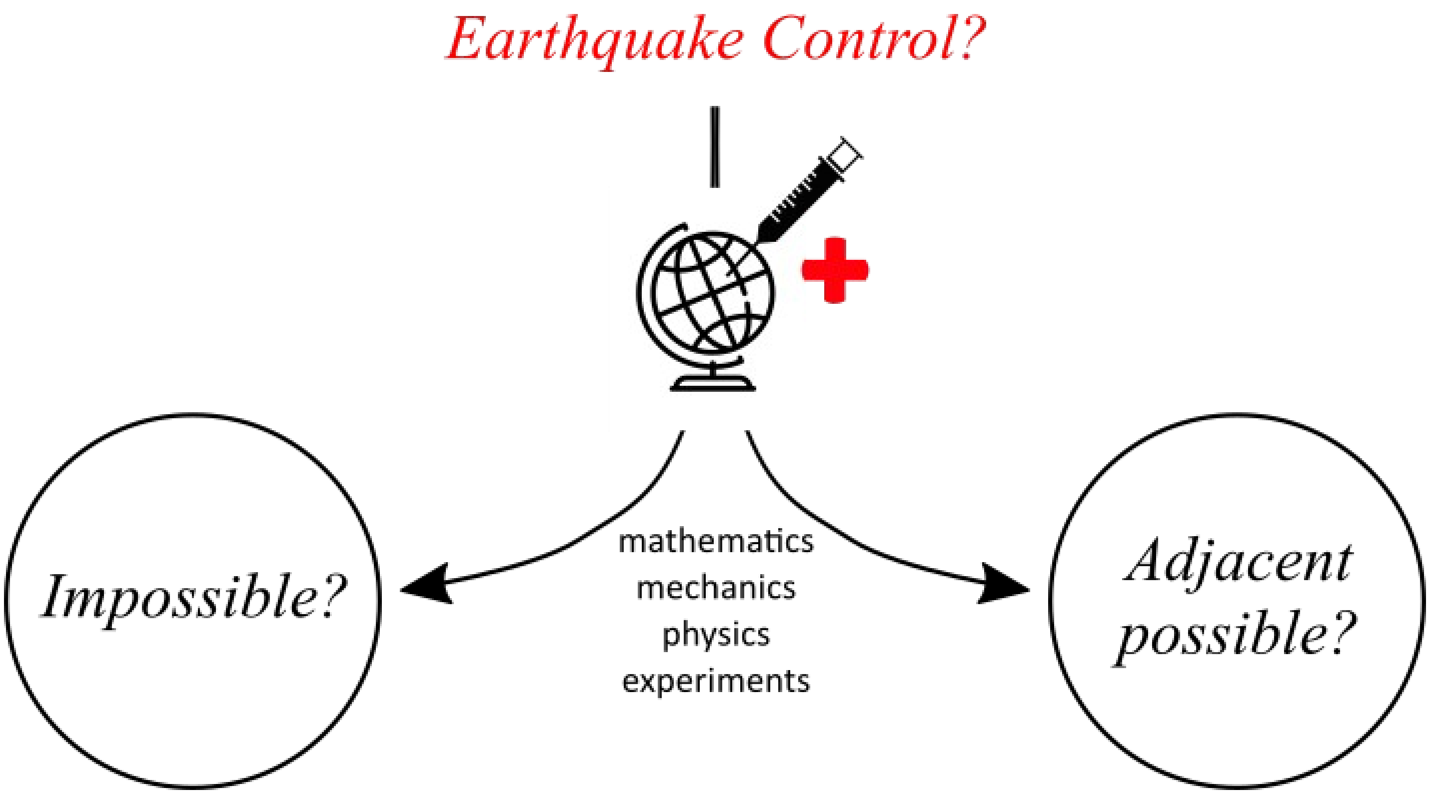
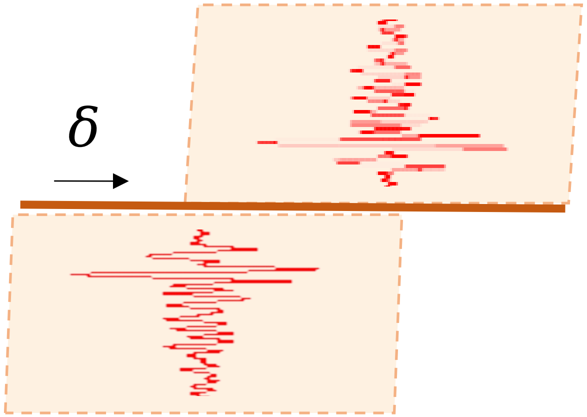
CoQuake.com

Context



Earthquake Control?
Impossible?
mathematics
mechanics
physics
experiments
Adjacent
possible?

Earthquakes in simple words



It is mathematically proved that:

CoQuake.com

If:

1) The friction coefficient is Lipschitz continuous w.r.t. the states x (fault slip & slip-rate) :

$$||\mu(x,t) - \mu(0)|| < \beta \, ||x||, \; \beta > 0$$

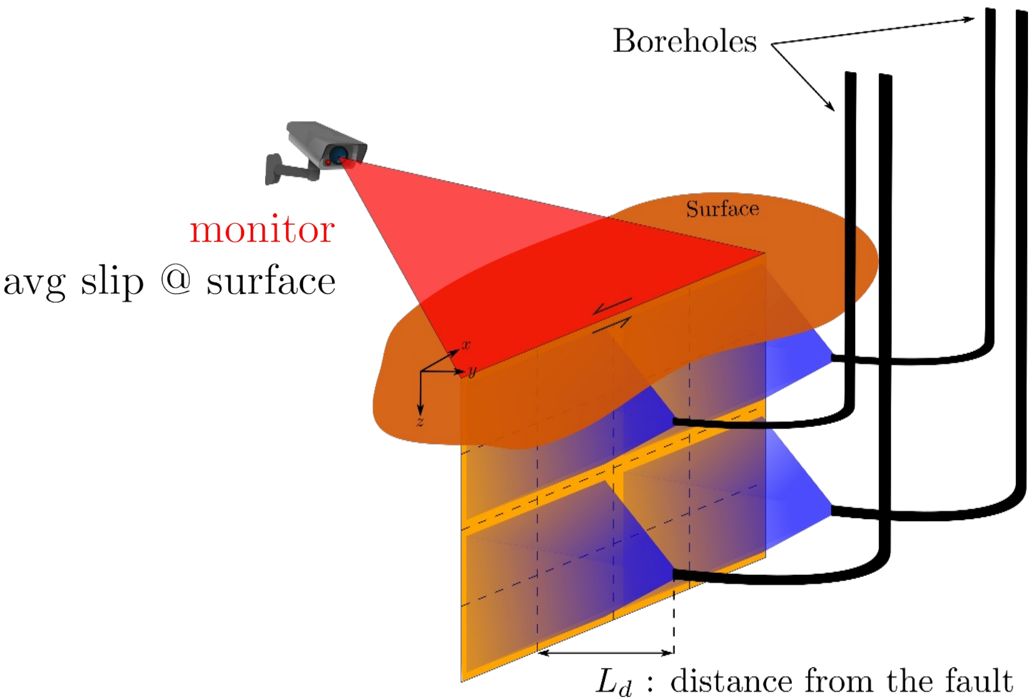
2) The friction coefficient has a lower bound: $\mu(x,t) > c > 0$

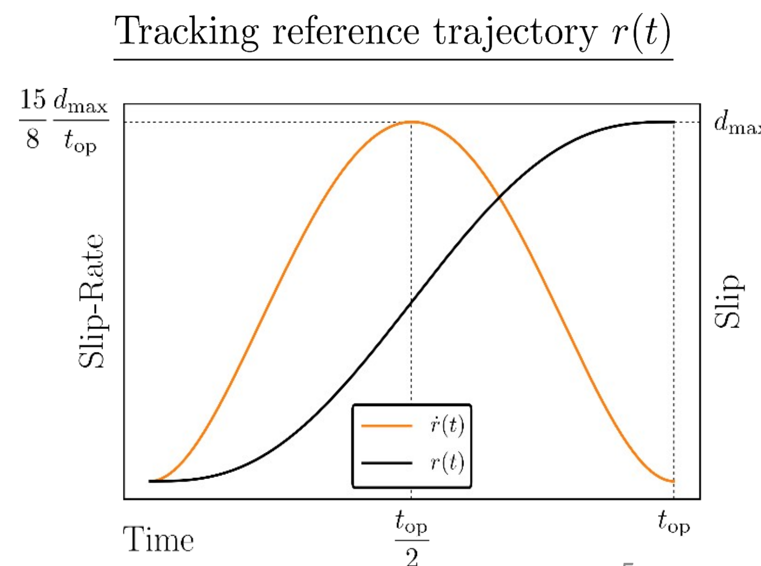
3) Diffusivity has a lower bound (greater than zero)

then we can control earthquake slip and prevent earthquakes.

(patent pending)
[Stefanou, 2019, JGR;
Stefanou & Tzortzopoulos, 2021, submitted;
Guttierrez et al., under preparation]

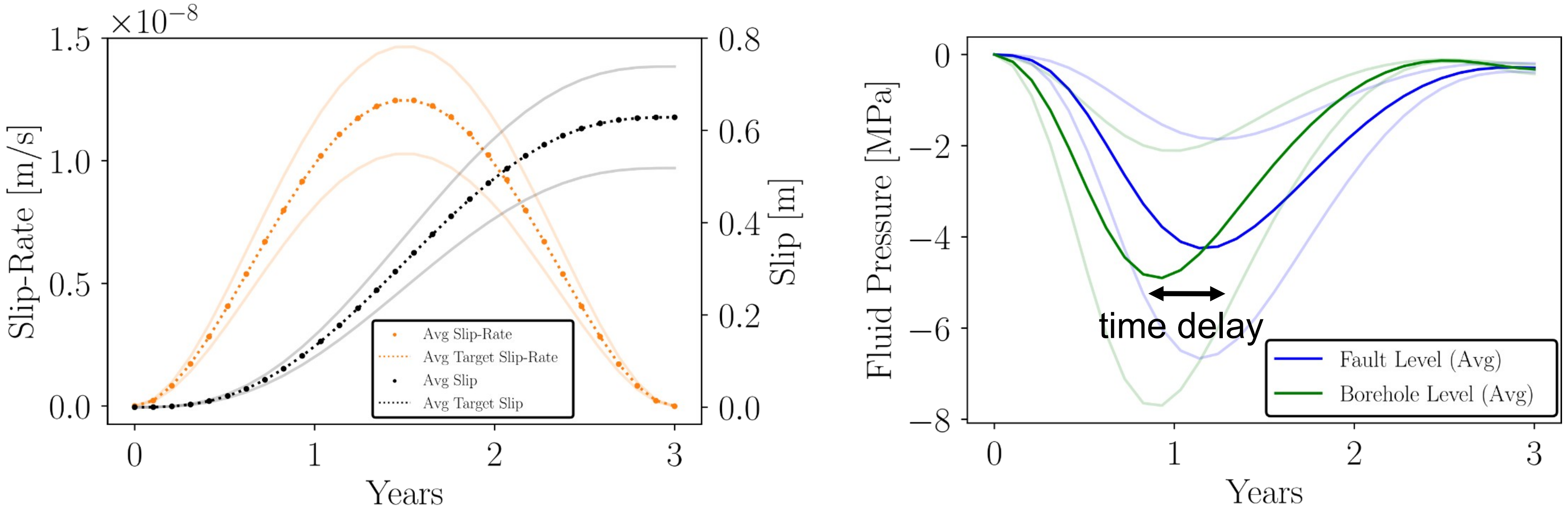
An example of EQ control





[Stefanou & Tzortzopoulos, submitted
Tzortzopoulos & Stefanou, under preparation]

EQ control with a grid of 4 injection points at 2.5km from the fault

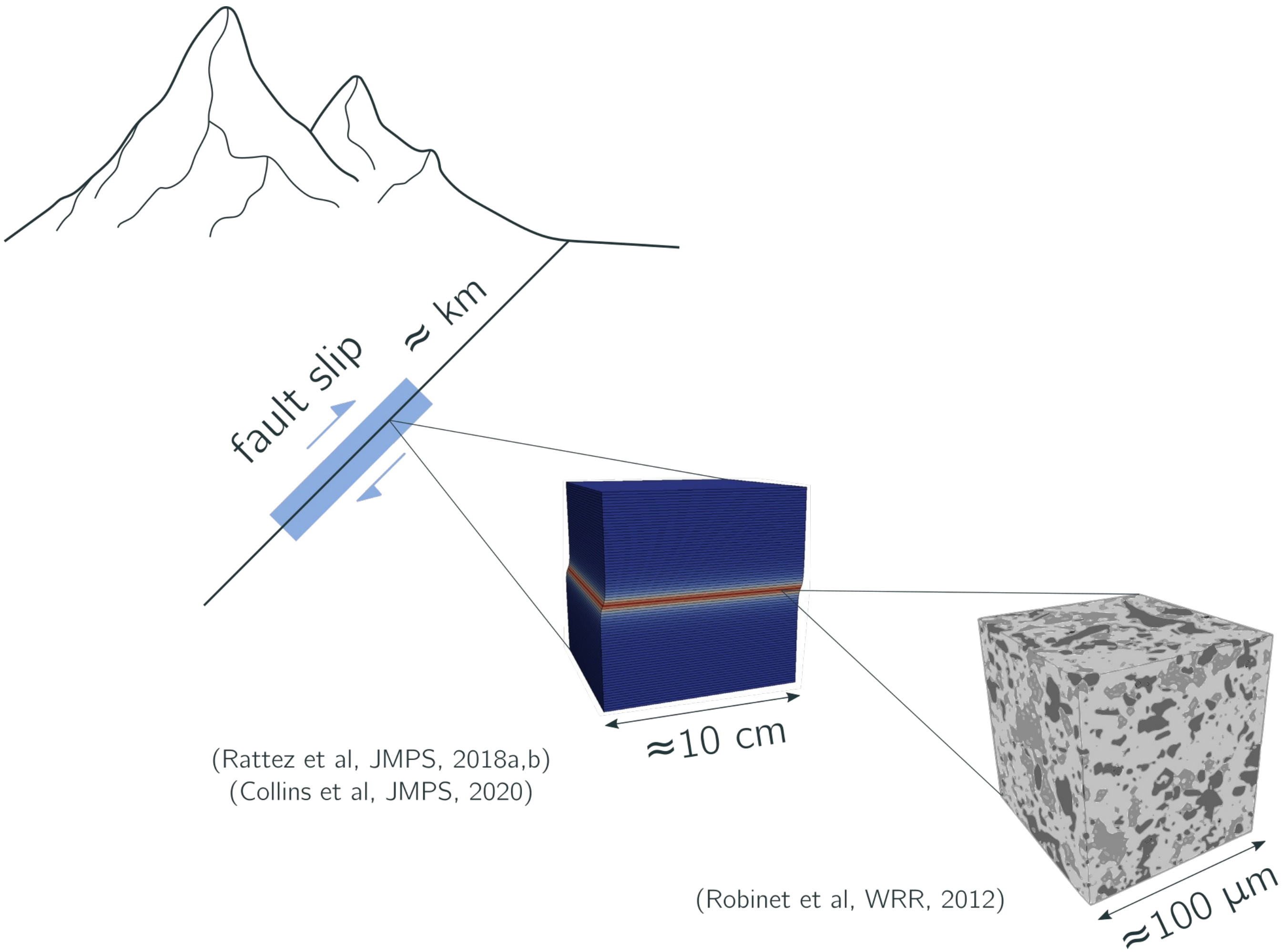


Agnostic to frictional properties and optimality

Control is possible even if we don’t know the exact frictional rheology of the fault!

BUT the more knowledge we have about friction
the more optimal our control design can be.

Studying fault friction



(Rattez et al, JMPS, 2018a,b)
(Collins et al, JMPS, 2020)

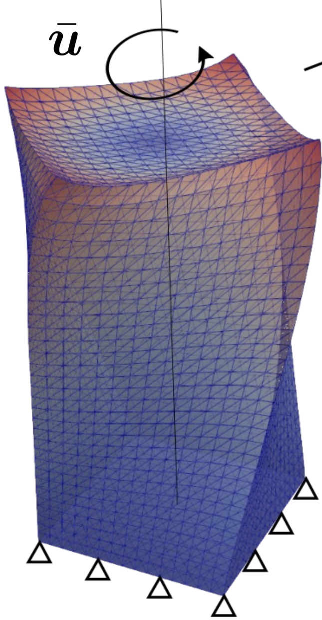
(Robinet et al, WRR, 2012)

complex materials; multiple inherent spatio-temporal scales

Bridging the scales

Macro-scale

Boundary Value Problem (BVP)



F

strain

FE^2
FEM×DEM
FEM×...

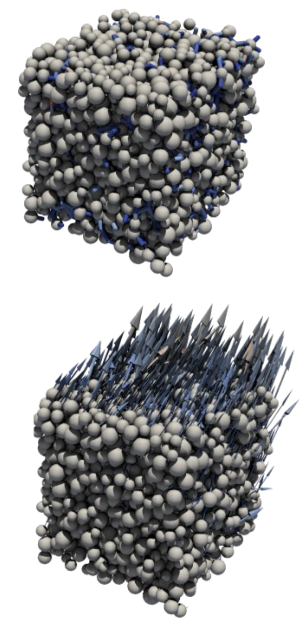
stress

S

micro-scale

auxiliary problem

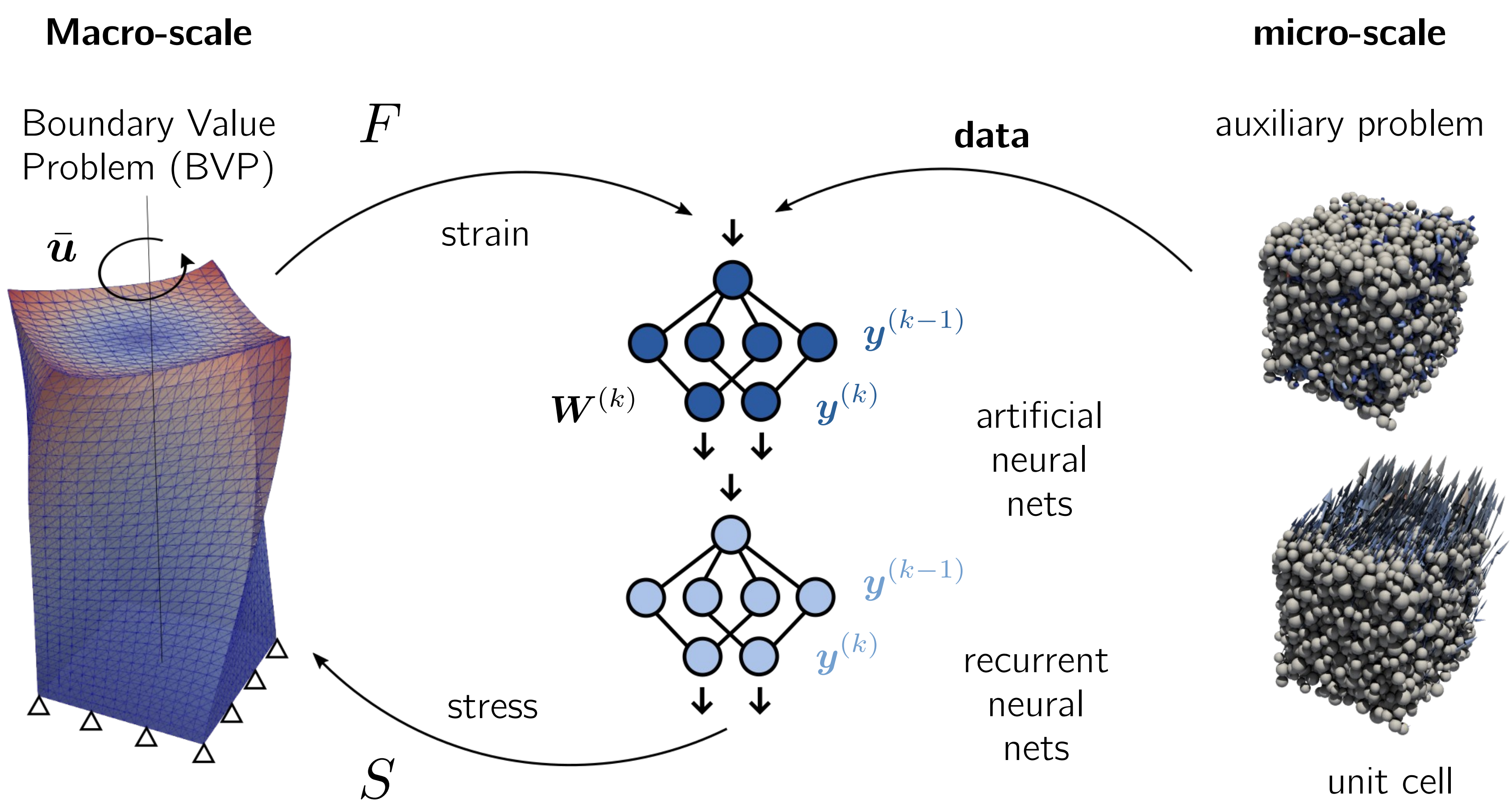
bottleneck
∀ point, time



unit cell

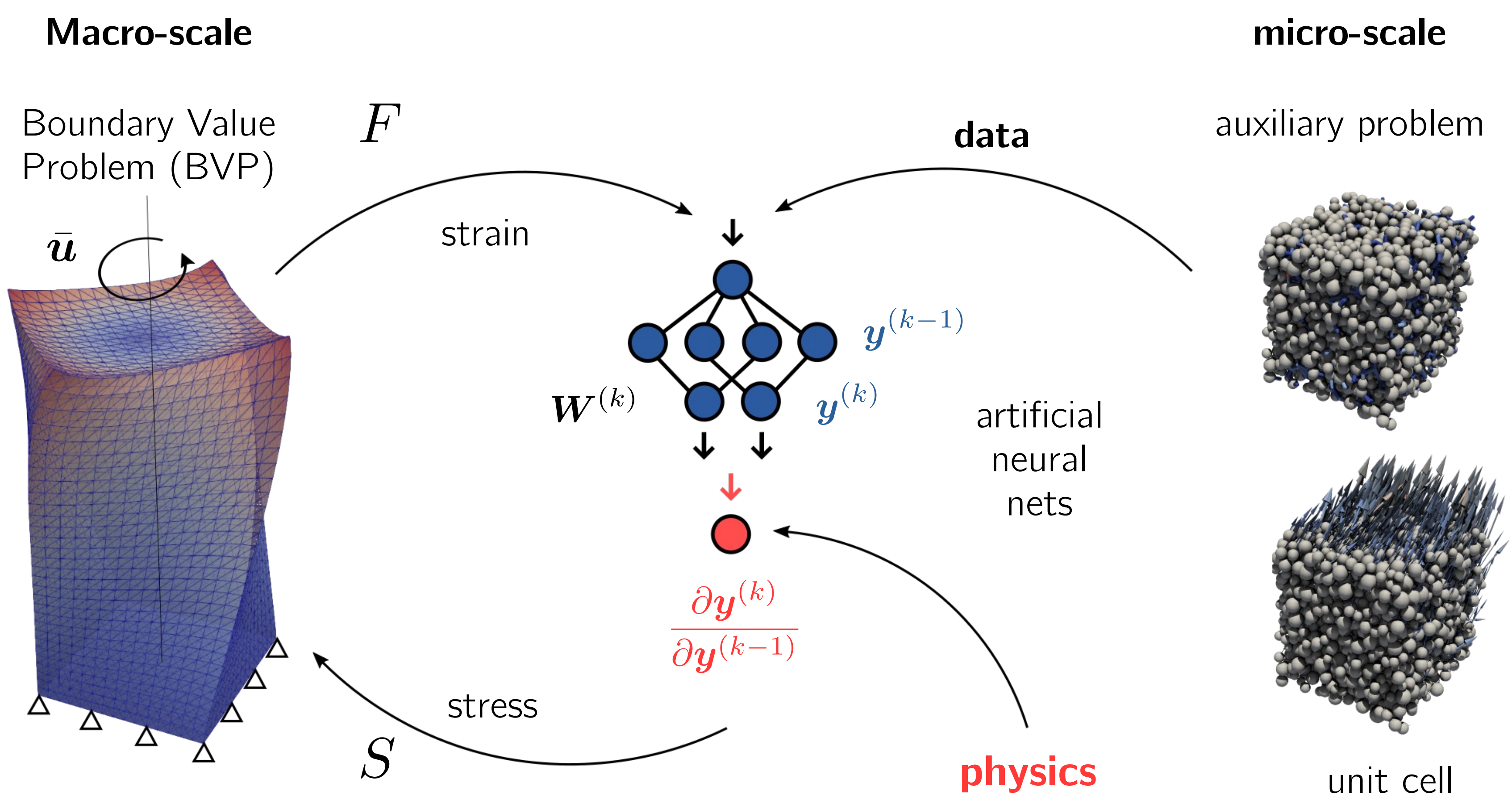
[Pinho-da Cruz et al, 2009]

Bridging the scales



[Ghaboussi et al, 1991
Lefik and Schrefler, 2003
Mozaffar et al, 2019
Mianroodi et al, 2021]

Bridging the scales



[PINN Karniadakis et al, 2019]

Thermodynamics-based ANN (TANN)
[Masi et al, 2021]

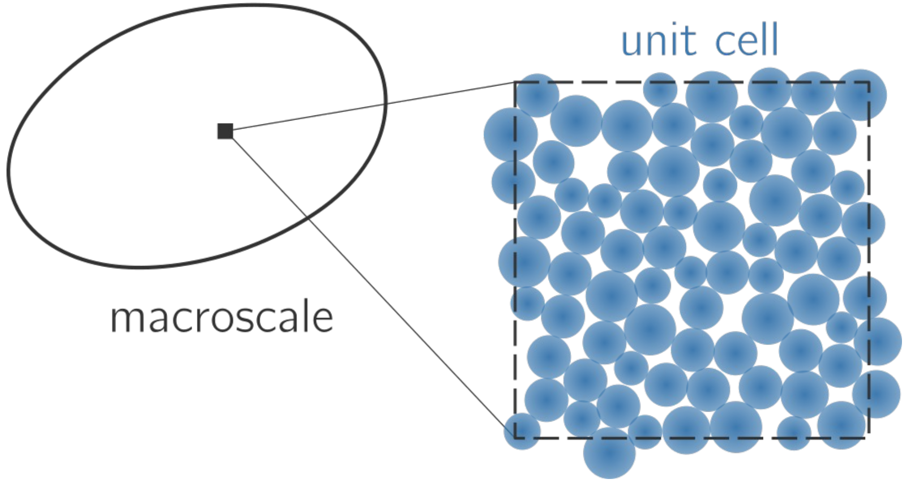
Adding physics: Thermodynamics

$$d = s : f - \dot{\psi} - \dot{\theta}\eta$$

d	mechanical dissipation rate	ψ	free-energy
s	1^{st} Piola-Kirchhoff stress	η	entropy
f	deformation gradient	θ	absolute temperature

Volume average 1^{st} and 2^{nd} law of thermodynamics

$$D = S : \dot{F} - \dot{\Psi} - H\dot{\Theta} \geq 0$$



Volume avg.

$$Y = \langle\, y \,\rangle = \frac{1}{|\mathcal{V}|}\int_{\mathcal{V}} y \, dx$$

$$\Psi = \Psi\left(\Theta, F, Z\right)$$ **internal State Variables**

[Coleman&Gurtin, 1967]

$$\dot{\Psi} = \frac{\partial \Psi}{\partial \Theta}\dot{\Theta} + \frac{\partial \Psi}{\partial F} : \dot{F} + \sum_{k=1}^{N_{ISV}} \frac{\partial \Psi}{\partial Z_k} \cdot \dot{Z}_k$$

$$D = S : \dot{F} - \dot{\Psi} - H\dot{\Theta}$$

Admissible thermodynamic processes have to respect:

$$\boxed{S = \frac{\partial \Psi}{\partial F}}$$

stress

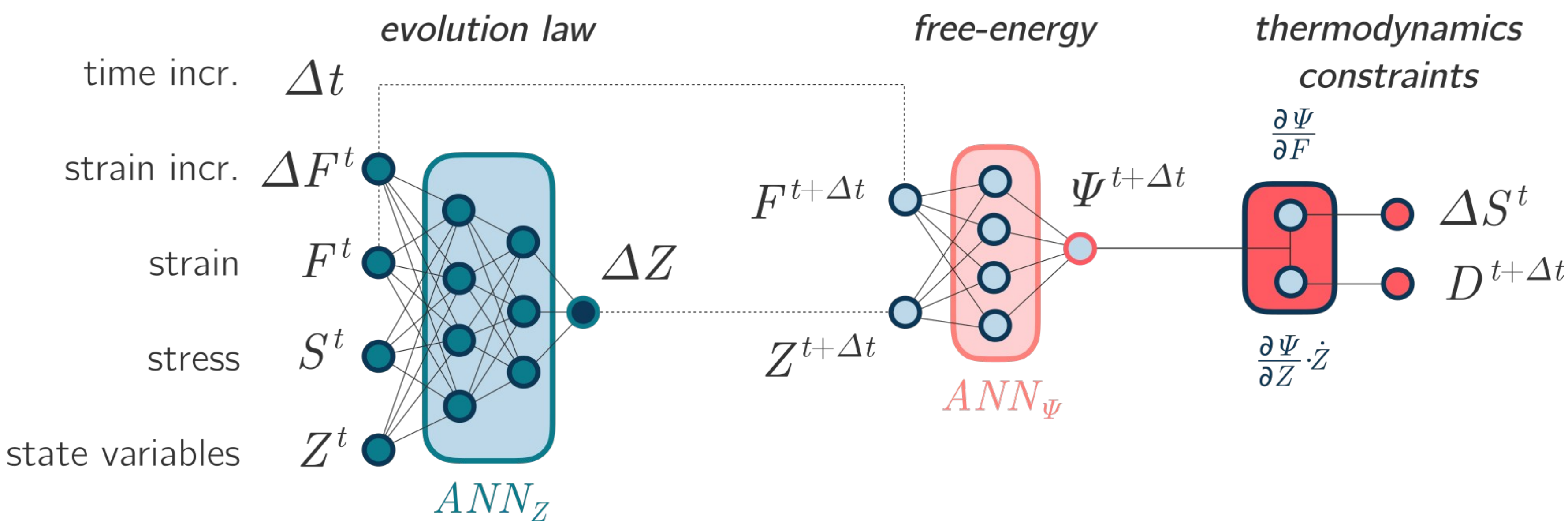
$$H = -\frac{\partial \Psi}{\partial \Theta}$$

entropy

$$\boxed{D = -\sum_{k=1}^{N_{ISV}} \frac{\partial \Psi}{\partial Z_k} \cdot \dot{Z}_k \geq 0}$$

dissipation rate

Thermodynamics-based ANN (TANN)



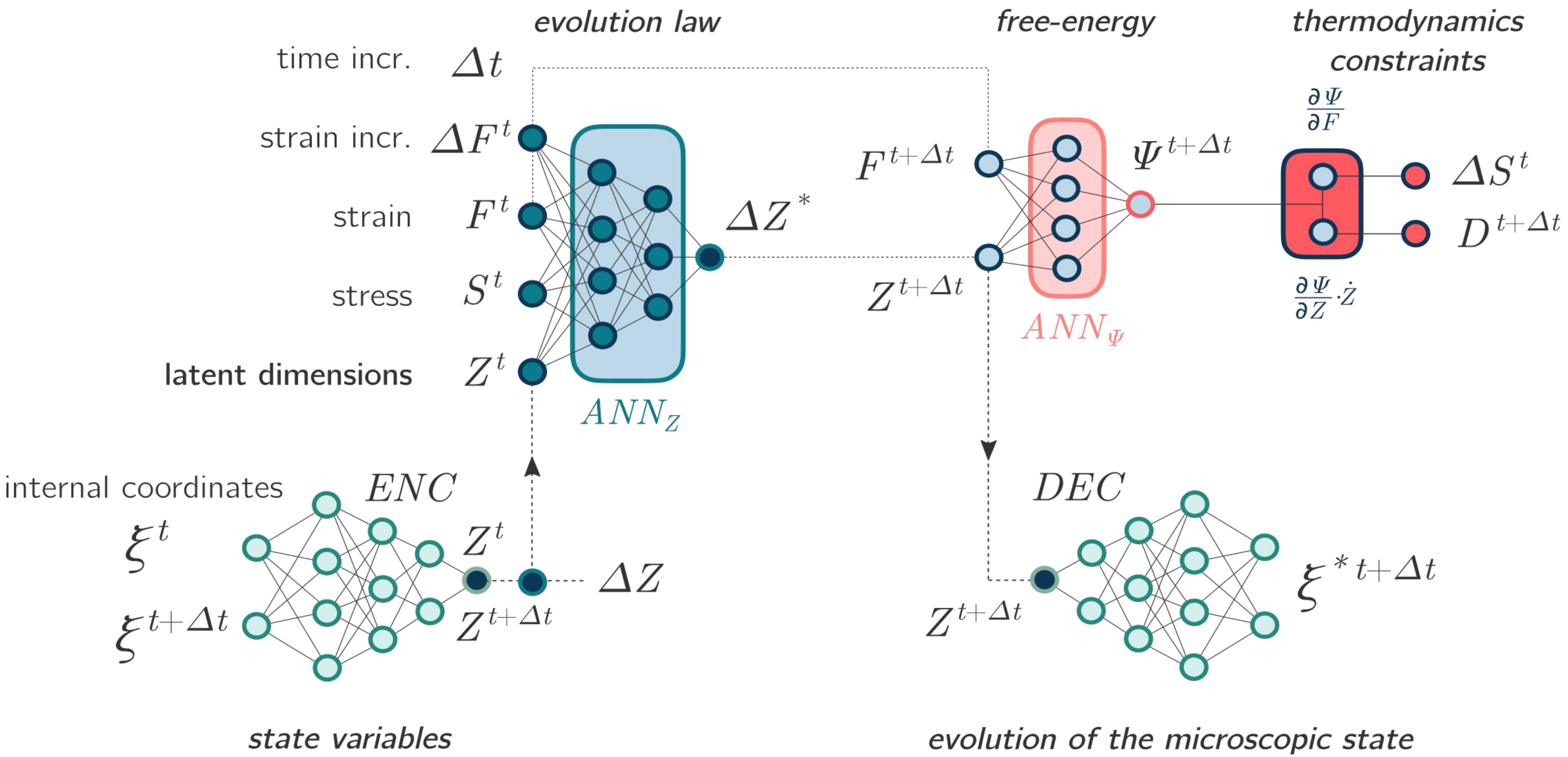
$$S = \frac{\partial \Psi}{\partial F}$$

stress

$$D = -\sum_{k=1}^{N_{ISV}} \frac{\partial \Psi}{\partial Z_k} \cdot \dot{Z}_k \geq 0$$

dissipation rate

Identifying state variables for complex materials



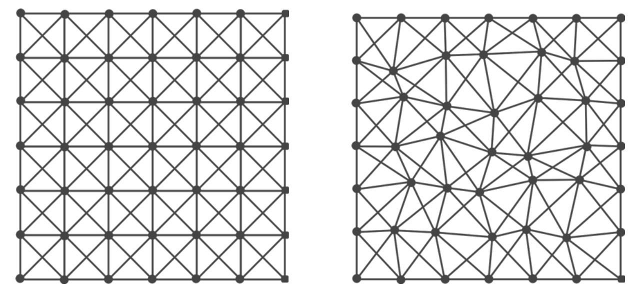
[Masi&Stefanou, arXiv:2108.13137 2021]

Benchmark

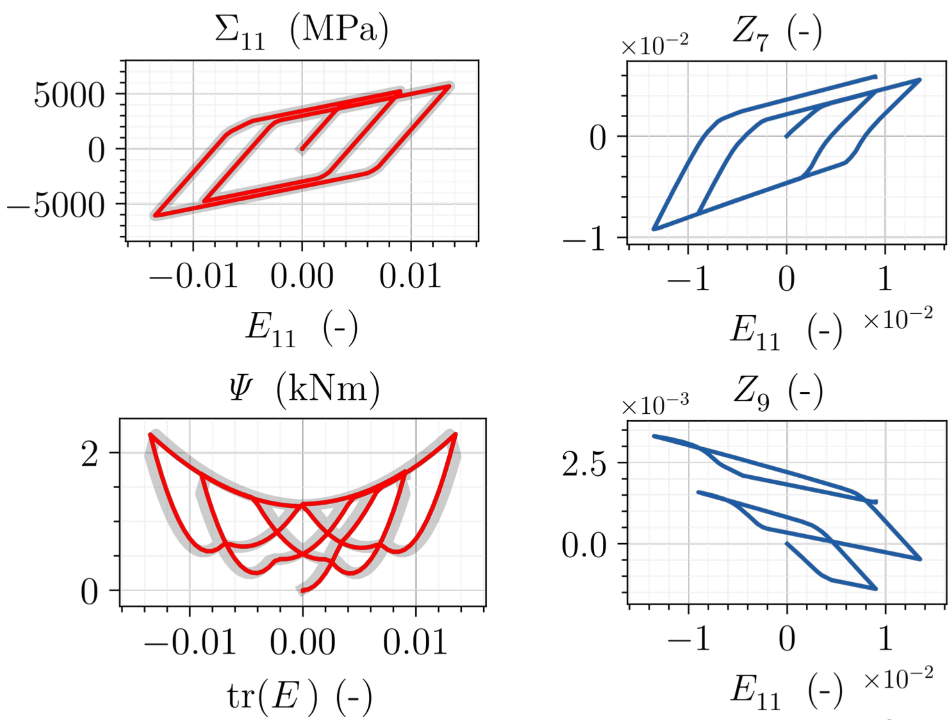
- In-house FE code (Numerical GeoLab)
- training on micromechanical datasets
- generated from random loading paths

[Stefanou, 2018]

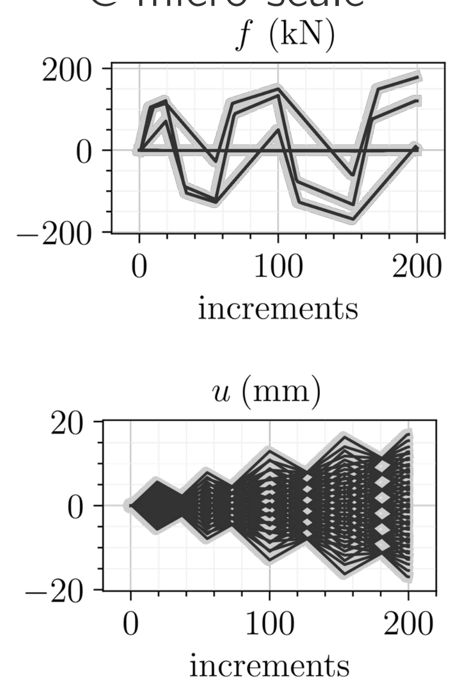
lattice structures



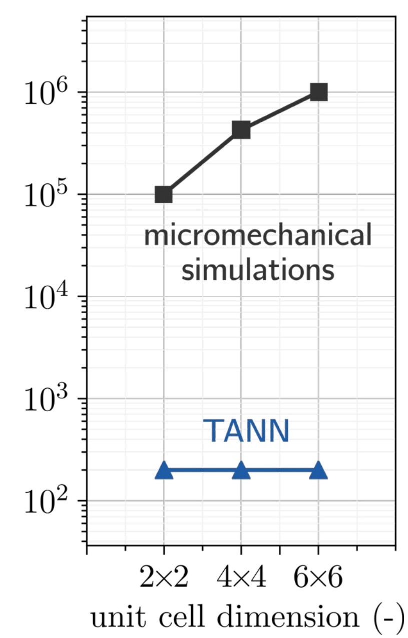
stress, energy, and *state variables*



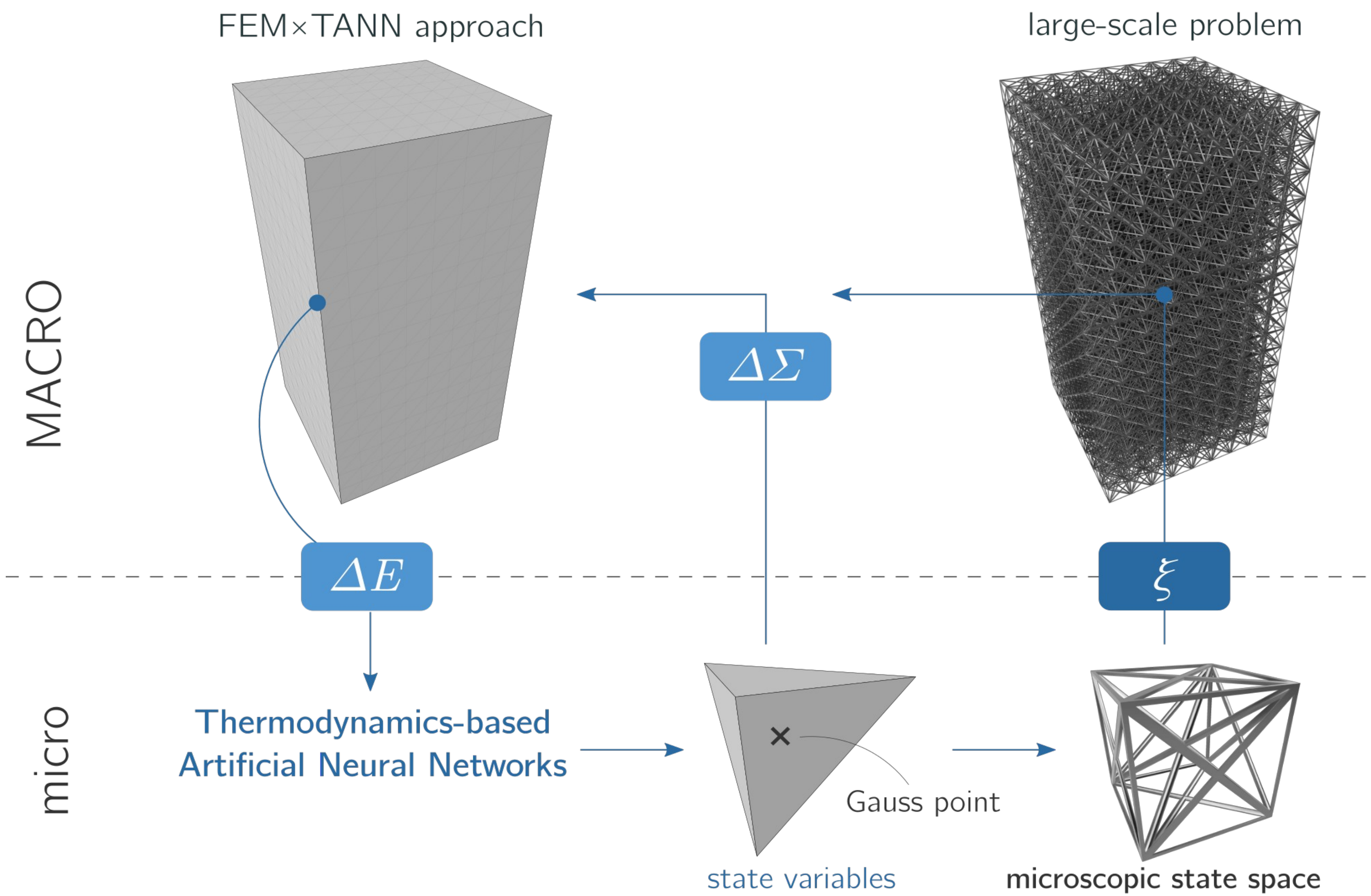
forces
and displacements
@ micro-scale



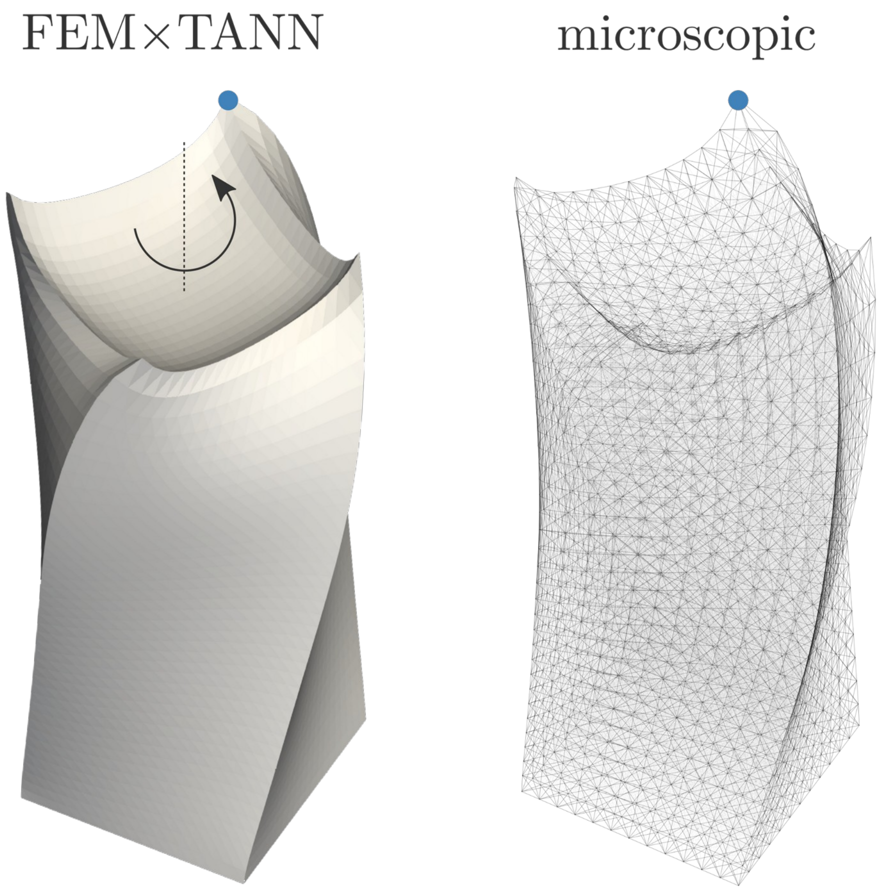
computational
cost

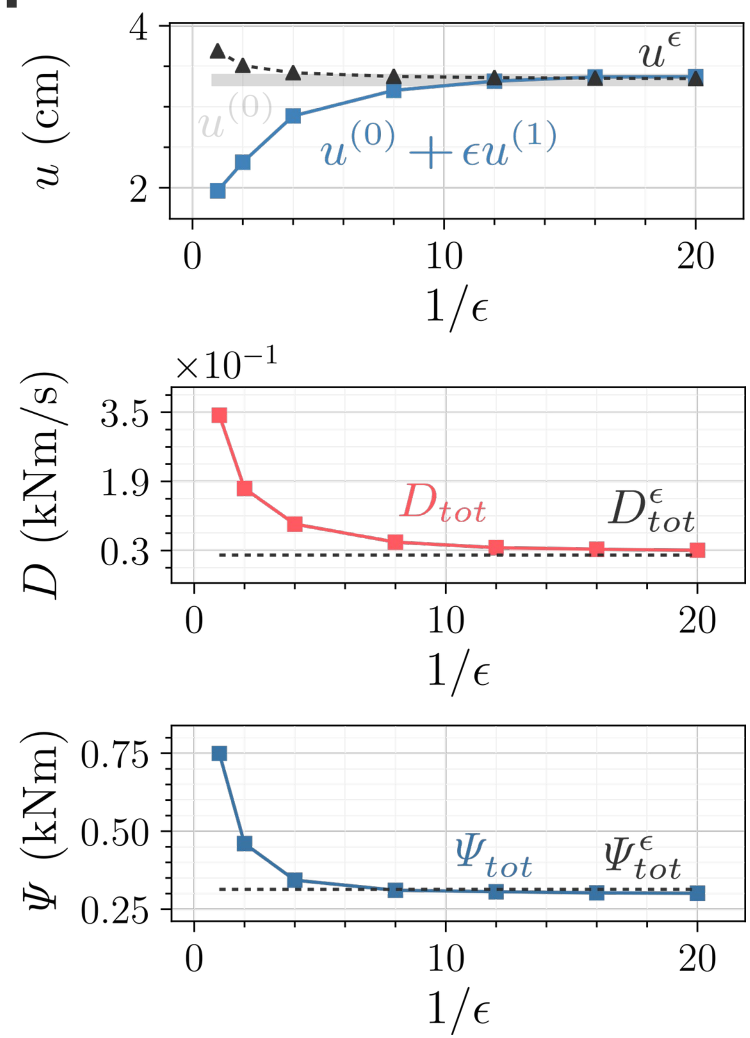


Large-scale problem – The FEM×TANN approach



Applications - Running on a laptop



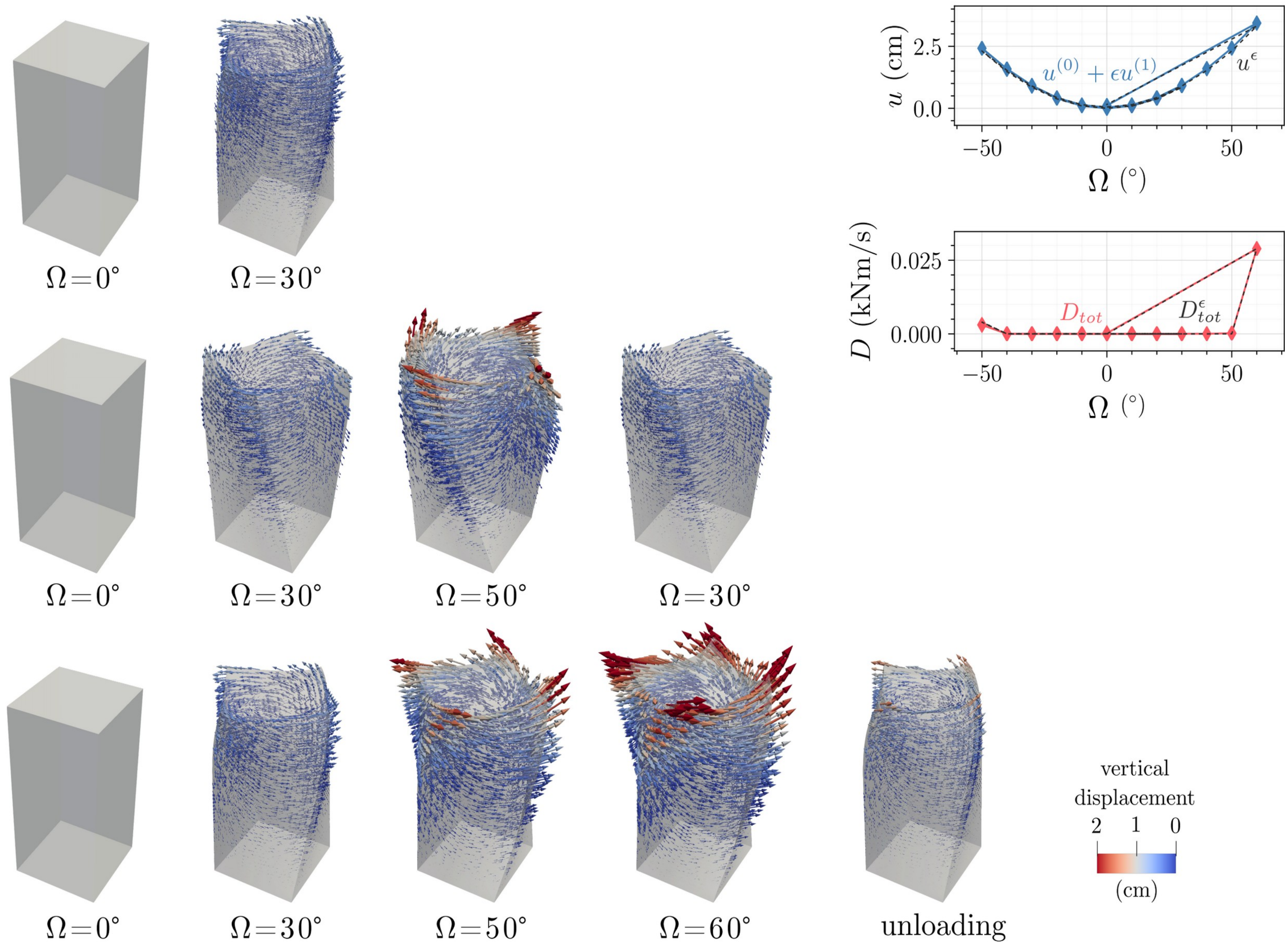


✓ Accurate and reliable simulations

✓ Reduced computational cost

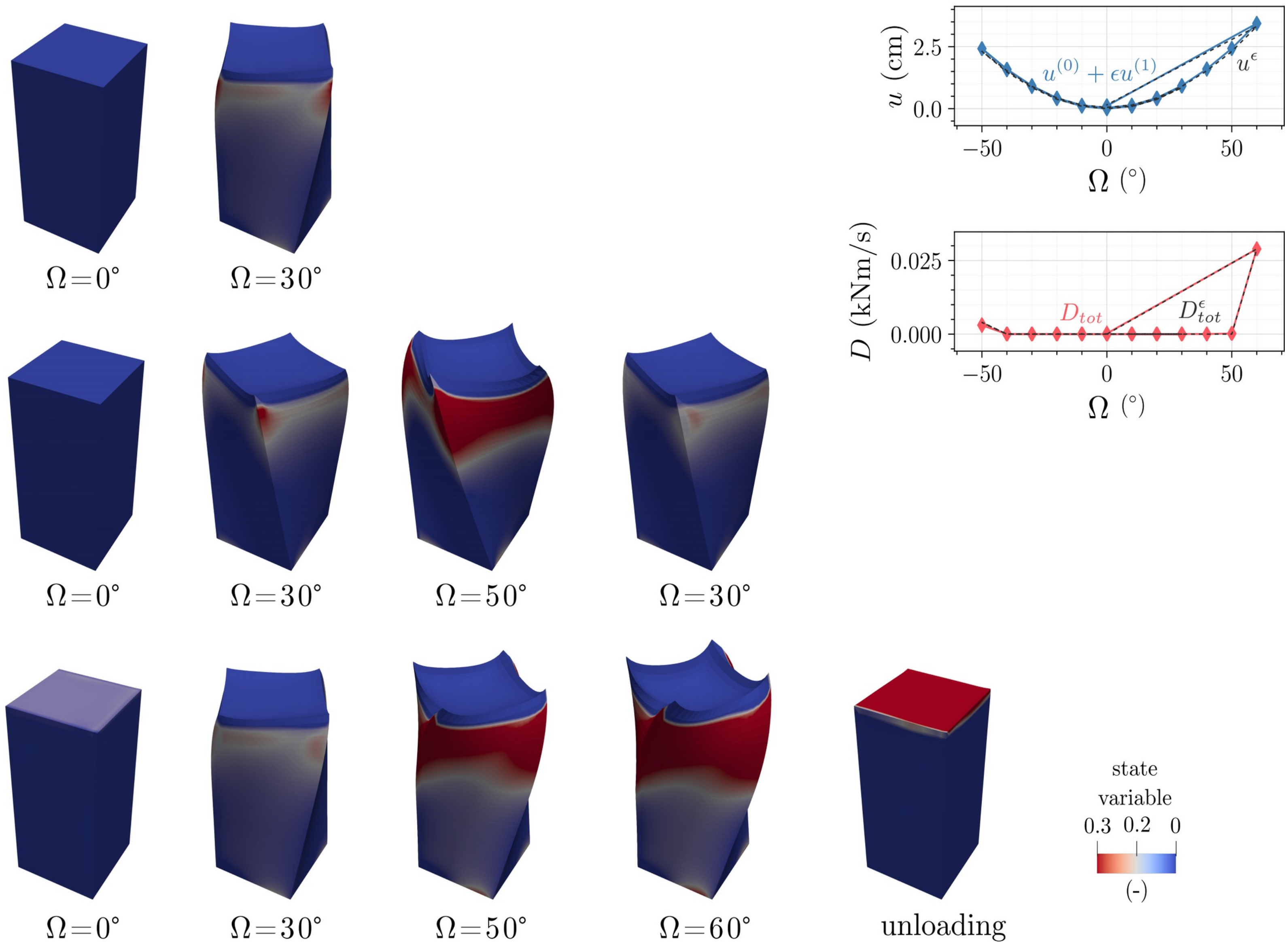
(enormous speed up!)

Some colors!



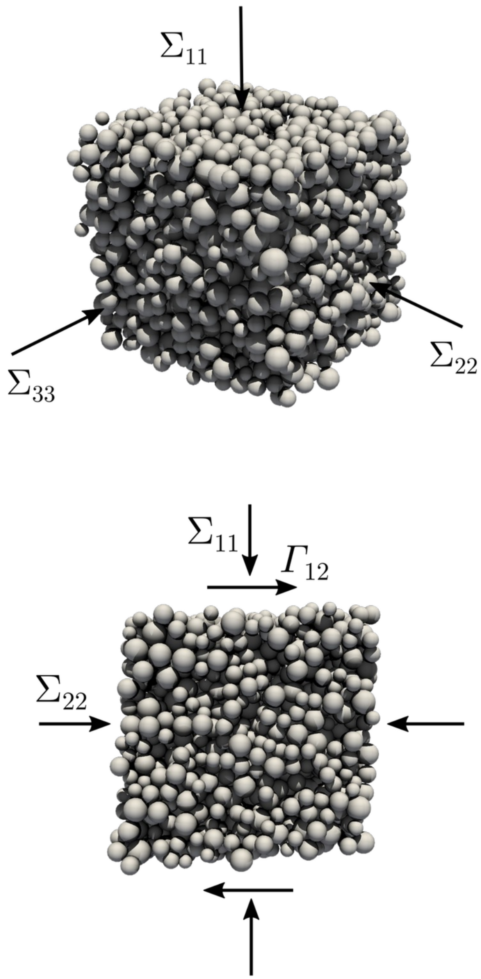
u (cm)
2.5
0.0
$u^{(0)} + \epsilon u^{(1)}$
u^{ϵ}
−50
0
50
Ω (°)
D (kNm/s)
0.025
0.000
D_{tot}
D^{ϵ}_{tot}
−50
0
50
Ω (°)
$\Omega = 0°$
$\Omega = 30°$
$\Omega = 0°$
$\Omega = 30°$
$\Omega = 50°$
$\Omega = 30°$
$\Omega = 0°$
$\Omega = 30°$
$\Omega = 50°$
$\Omega = 60°$
unloading
vertical displacement
2 1 0
(cm)

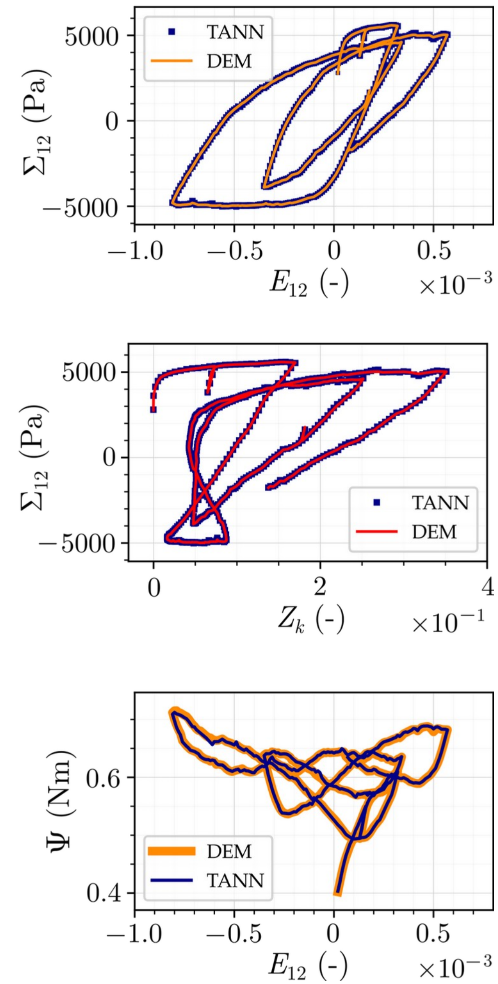
More colors!



$\Omega = 0°$
$\Omega = 30°$
$\Omega = 0°$
$\Omega = 30°$
$\Omega = 50°$
$\Omega = 30°$
$\Omega = 0°$
$\Omega = 30°$
$\Omega = 50°$
$\Omega = 60°$
unloading
state variable
0.3 0.2 0
(-)
u (cm)
2.5
0.0
-50
0
50
Ω (°)
$u^{(0)} + \epsilon u^{(1)}$
u^{ϵ}
D (kNm/s)
0.025
0.000
D_{tot}
D^{ϵ}_{tot}

Applications to granular media (and soon faults)

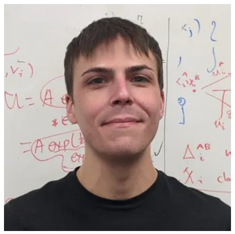




Summary

- Thermodynamics-based ANN (TANN) provide **thermodynamically consistent predictions**. This is central in engineering.
- They **accelerate training** as intrinsic physics do not need to be learned.
- **Internal state variables are automatically identified** based on microscopic quantities.
- By feature extraction they can **shed light to micro-mechanisms** that otherwise would be hard or impossible to study.
- They **enable large, multi-scale simulations of complex inelastic materials on a laptop**.
- They can find **numerous applications**, e.g. rock mechanics, fault mechanics and earthquake control.

Thank you!

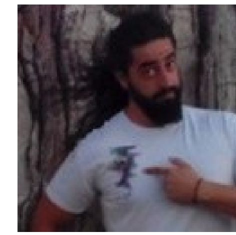

Dr Filippo Masi


Dr Georgios Tzortzopoulos

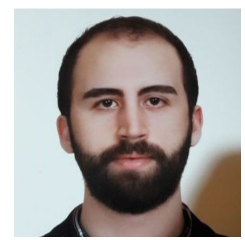

Dr Alexandros Stathas

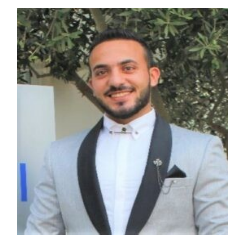

Dr Diego Guttiérez-Oribio


Dr Philpp Braun


Dr Timos Papachristos


Dr Pravin Bararayanni


Abdallah Aoude


Ahmad Morsel

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TEDx Talk: https://youtu.be/9JXdv-3e2bc

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