Al applied to ODEs and PDEs

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Applying AI to non-linear Physics

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1: Presentation of the team

Merging of PCiAI and PATP

- Sadri Benkadda
- Peter Beyer
- Mohammed Koubiti
- Nathaniel Saura
- David Garrido
- Active collaboration with CEA, Osaka University, American University of Beyrouth
- Future collaboration with Tokyo University, University of Seattle, ...

Plasma and fusion

- \circ Instead of nuclear fission, **nuclear fusion** ⇒ more energy, less radioactivity but: extreme conditions, non-linearity, turbulence...
- Tokamak: fusion reactor. Strong magnetic fields instead of gravity.
- **Confinement**: keeping the plasma's central region sufficiently hot and dense for nuclear fusion.
- Achieving efficient nuclear fusion: maintaining high confinement mode ⇒ more energy produced
- **Impurities**: weakly ionized ("cold") atoms torn from the Tokamak walls due to its interactions with the hot plasma
- $\,\circ\,$ Impurities migrate from wall to core this breaks the confinement

Our topics

Our main focus

- Applying AI to overcoming the fusion's barriers
 - Towards understanding the origin of the degradation of the confinement
 - Remove signal corruption to enhance measurement devices
 - $\bullet\,$ Better identify "cold elements" coming from the edge $\Rightarrow\,$ control
 - Speed up simulations and/or develop models
- Non-linear physics (Astrochemistry, Fluid mechanics)

Secondary topics

- Application of AI in Ecology
- Modeling energy community evolution using game theory
- Automatic molecular identification

Improving the identification of ions in the presence of strong noise

- In spectroscopy, the noise degrades the accuracy and confidence of element recognition methods
 - Corrupts data
 - Challenges the usability of signal processing methods
- $\,\circ\,$ CNN have been widely used in the context of noisy images
 - Disentangling noise and signal to keep the coherent part
 - Auto-encoder (CAE) vs Denoising CNN (DnCNN) based on residual

Use and compare CNN architectures to improve the ion identification

Considering strongly corrupted signals:

- Improve the PSNMF identification confidence using the two approaches
- Compare the noise removing capacity and the learning strategy induced by the architecture

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Figure 1: DnCNN [?] and the enhanced one [?] featuring a residual connection.



Figure 2: CNN Encoder-decoder architecture example [?]

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Signal denoising comparisons (N0; SNR = -1)



Figure 3: Denoising comparisons for N0

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Signal denoising comparisons (W2; SNR = -1)



Figure 4: Denoising comparisons for W2

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Figure 5: Noise described by SNR = -1

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PSNMF improvement (SNR=-5)



Figure 6: Noise described by SNR = -5

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AiPoG - Global Framework



Figure 7: Framework: how to tackle PDEs

Learning the dynamics of a system

Using a well-designed neural network, we can learn the time rate evolution of a system

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Dynamical system: Predator-Prey

$$\begin{split} \frac{dE}{dt} &= 2E\left(\gamma - \alpha_1 E - \alpha_2 U\right), \\ \frac{dU}{dt} &= 2U\left(-\mu + \alpha_3 E\right). \end{split}$$



Figure 8: Training to learn the system's dynamics



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Example of AiPoG on Hasegawa-Wakatani



Figure 10: Training to learn the ODE systems obtained from the Galerkin Projection onto the extracted POD modes Presentation of the team 000

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Example of AiPoG on Hasegawa-Wakatani



Figure 11: Comparison of expected and predicted fields

Ongoing and future works

- Improving AiPoG application to chaotic systems and other PDEs
- Predicting particle cluster with specific properties
- Enhancing spectroscopic analysis (CEA)
- Developing a machine-learning-based interatomic potentials (Osaka University)
- Automatic identification of a molecule and its atomic composition (ASTRO, Osaka University)
- Application of Game Theory to enhance interpretability of NN
- And more

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