**Taming nuclear complexity using a Committee of Deep Neural Network**

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Quantum many-body systems and especially atomic nuclei are intrinsically complex systems. This complexity prevents analytical descriptions of nuclear properties while spanning an impressive range of emerging phenomena (deformation, pairing, clustering...). The unified description of these phenomena is still a challenge after several decades of research and despite the outstanding progress of ab-initio techniques, EDF (Energy Density Functionals) remains state-of-the art method to encode most of these phenomena all over the nuclear chart in spite of several flaws of this approach [1-2]. We thus might try to imagine new way to understand nuclear properties.

With the exponential development of fancy Machine Learning techniques we might want to boldly ask: Is a Machine is able to understand (almost) on its own the physics of the nuclei?

Nowadays more and more Artificial Intelligence techniques are used to tackle physics problems [3-4] for which they are giving promising results. However these approaches are frequently considered as ''black-box" which is both a huge technical and philosophical issue.

We have developed a new neural-network based approach to predict several nuclear observables while trying to keep an understanding of the underlying neural processes [5].

In the first part of this talk we will present the fundamentals and computational interests of this approach as neural-networks seem well tailored systems to describe emerging features. Then in the second part, we will introduce several tools and quantities which are able to provide some hints on the processes performed by our Network to produce accurate results, and might be able to teach us some new ways to investigate nuclear structure. Finally we will present our approach as an efficient tool allowing experimentalists to obtain very quickly predictions for several observables of interest (Mass, Radii, Spectrum).

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[4] W. Ye, C. Chen, Z. Wang, I. Chu, S.P. Ong, Nature Com. Vol 9, 3800 (2018).
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