

Marie Skłodowska Curie Action –Postdoctoral Fellowship 2025 (MSCA-PF-2025)

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Department /Institute /Centre Name	Departamento de Matemática Aplicada a la Ingeniería Industrial
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Province	Madrid
Research Area	Information Science and Engineering (ENG) Mathematics (MAT) Physics (PHY)
Brief description of the Centre/Research Group	Our research group is interested in the study of modern machine learning techniques through the lens of statistical mechanics and disordered systems theory. We are leaders in the study of energy- based generative models and, in particular, in the analysis and use of Boltzmann machines. We are engaged in a wide range of studies, from the fundamental understanding of how generative models encode patterns during the learning process to the improvement of training protocols and architectures using insights from computational and statistical physics. In addition, we are dedicated to developing a new generation of inference tools that facilitate the extraction of clear, interpretable information from large data sets, with a particular focus on practical biological applications. These efforts also aim to increase the transparency and interpretability of neural networks to ensure their responsible and sustainable use in scientific research.
Project description	 Data-driven applications of Restricted Boltzmann machines (RBMs) in bioinformatics and neuroscience. RBM are versatile models of generative Machine Learning. We can use this model on real dataset, particularly biologically-oriented, where the lack of samples and good conditioning can be handled quite well with the RBM. Using developed tools of the group and eventually new ones for specific purpose, the goal is to study functions, or statistical properties of these datasets and show their relevance with respect to the field of application. Leveraging RBMs for Efficient Simulations of Physical Systems. RBM can be used to map its probability distribution onto complex physical models. This can be then leverage thanks to the bipartite structure that helps to accelerate simulations.
	 Development of new generative models, training protocols, and interpretative tools. The natural extension of RBM is to consider the addition of hidden layers to form more expressive models that can possibly extract higher order features, with the possibility to extract information from the learned dataset. This goes with the development of innovative training process and analytical understanding.



	 Theoretical Analysis and Parameter optimization of simple neural network models. RBM are complicated models, although it is still possible to perform analytical computation thanks to his bipartite structure. The learning dynamics still need to be characterized with more precision to understand how patterns are formed under the training process. Theoretical insights about the effects of limited and/or corrupted data. Understanding how the RBM can leverage federated learning, the learning of various models coupled together or corrupted dataset. These tasks can be tackle both analytically and numerically.
Applications: documents to be submitted and deadlines	CV, letter of motivation, reference letters, one or two pages of research lines for the fellowship. Deadline: 30 th April 2025