CS PhD Seminar Series

Oct 21st | 14:30-15:30 | Room 214

Deep Equilibrium Models for Poisson Inverse Problems via Mirror Descent

Inverse problems in imaging arise in a wide range of scientific and engineering applications, including medical imaging, astrophysics, and microscopy. These problems are inherently ill-posed, requiring advanced regularization techniques and optimization strategies to achieve stable and accurate reconstructions. In recent years, hybrid approaches that combine deep learning and variational methods have gained increasing attention. Well-established techniques include Algorithmic Unrolling, Plug-and-Play methods, and Deep Equilibrium Models. The latter are networks with fixed points, which are trained to match data samples from a training dataset. In this work, we focus on Deep Equilibrium Models to learn a data-driven regularization function for Poisson inverse problems, using the Kullback-Leibler divergence as the data fidelity term. To effectively handle this fidelity term, we employ Mirror Descent as the underlying optimization algorithm. We discuss theoretical guarantees of convergence, even in non-convex settings, incorporating a backtracking strategy, along with key aspects of training this class of models. To validate our approach, we evaluate its performance on a deblurring task with different kernels and varying levels of Poisson noise.

Speaker: **Christian Daniele**

I'm a PhD student at MaLGA center in Genoa, affiliated to Genoa University. I've been working on Inverse Problems with applications in Microscopy, developing optimisation-driven learning methods. In particular my ongoing work is about Deep Equilibrium Models to solve Poisson Inverse Problems.

Bridging Symbolic and Sub-symbolic AI in Explainable Autonomous Agents

Autonomous agents face a fundamental trade-off: symbolic systems offer interpretability but lack adaptability, while neural approaches excel at learning but operate as black boxes. Yet cognitive architectures can be understood as computational frameworks that guide sub-symbolic learning—enabling these paradigms to complement rather than compete. We reframe agent behavior as hierarchical computation where BDI reasoning (beliefs, desires, intentions) structures neural policy learning. Symbolic plans constrain exploration while neural networks handle sensorimotor control, enabling reasoning under uncertainty about environmental states and goal achievement. This integration is demonstrated across different tasks from discrete grid-world pathfinding to continuous environment.
Within this perspective, this enables how goal-driven symbolic reasoning and adaptive neural learning emerge as complementary approaches, providing a foundation for neuro-symbolic agents where transparency and performance coexist through hierarchical computational principles.

Speaker: **Zahra Daoui**

Zahra Daoui is a first-year PhD student in Computer Science at the University of Genoa. She obtained her Bachelor's degree in 2021 and a Master's degree in 2024 in Computer Science. She is working under the supervision of Professor Viviana Mascardi on integrating BDI agents with reinforcement learning for autonomous systems. The research activity is mainly focusing on the study of solutions for integrating symbolic reasoning with sub-symbolic learning in autonomous agents. The main research interests are multi-agent systems, cognitive architectures, and the intersection of symbolic reasoning with neural learning approaches in autonomous systems.