One of the central questions in star formation is the origin of the initial mass function (IMF), which governs stellar evolution. The IMF exhibits a peak around 0.1 $M_\odot$, suggesting the presence of a characteristic physical scale. Since stars form within dense cores of molecular clouds, the IMF is often linked to the dense core mass function (DCMF). Observations across a variety of clouds reveal a similar peak, with an efficiency of approximately 30% between dense core mass and the resulting stellar mass. However, recent studies indicate that this peak may be influenced by observational biases, such as limited resolution and the under-detection of low-mass cores.

My thesis aims to measure the DCMF using a novel approach based on deep neural networks. Given their increasing performance and success across many areas of physics, these methods provide a promising framework to identify and characterize dense cores, particularly low-mass ones, from molecular line and dust emission integrated along the line of sight.

In a first study, we investigate several neural network architectures (CNNs, diffusion models, and conditional invertible neural networks, cINNs) to estimate the mass-weighted average density using dust emission alone. We provide a systematic benchmark of these architectures, highlighting their respective strengths and limitations in this physically degenerate context. We find that cINNs accurately reproduce both the peak and the high-mass power-law slope of the core mass function inferred from existing core catalogs, although they are difficult to train and perform poorly in diffuse regions. In contrast, U-Net and diffusion-based models recover the high-mass power-law behavior but systematically underestimate the population of dense cores, while showing better performance in low-density environments.

The ultimate goal of this work is to extend this approach toward reconstructing a physically consistent three-dimensional structure of molecular clouds by combining multiple tracers, including molecular line and dust emission, within a multimodal deep learning framework.