# Deep Plug-and-Play Optical Priors for Ground-Based Point Spread Function Models

M2 Internship project, 2024

**Keywords:** *Machine learning, Inverse problems in imaging, Point spread function modelling*

## Internship synopsis

**Context.** Weak gravitational lensing [1] is a powerful probe of the Large Scale Structure of our Universe. Cosmologists use weak lensing to study the nature of dark matter and its spatial distribution. Weak lensing missions require highly accurate shape measurements of galaxy images. The telescope's instrumental response, or point spread function (PSF), produces a deformation of the observed images. This deformation can be mistaken for the effects of weak lensing in the galaxy images, thus being one of the primary sources of systematic error when doing weak lensing science. Therefore, estimating a reliable and accurate PSF model is crucial for the success of any weak lensing mission. The PSF field can be interpreted as a convolutional kernel that affects each of our observations of interest that varies spatially, spectrally, and temporally. The PSF model needs to be able to cope with each of these variations. We use specific stars considered as point sources in the field-of-view to constrain our PSF model. These stars, which are unresolved objects, provide us with degraded samples of the PSF field. The observations go through different types of degradations depending on the properties of the telescope. Some of these degradations include undersampling, an integration over the instrument's passband, and additive noise. We finally build the PSF model using these degraded observations and then use the model to infer the PSF at the position of galaxies. This procedure constitutes the ill-posed inverse problem of PSF modelling. See [2] for a recent review on PSF modelling.

There are several sources of spatial variations of the PSF. Some cover the focal plane like the optical aberrations of the telescope and the atmosphere, while others are specific for each Charge-Coupled Device (CCD) chip. The focal plane of current wide-field imaging cameras comprises a large array of CCDs. Most of the current PSF models are built independently on each CCD, which is a simple solution to account for both types of variations. However, this choice has some drawbacks. It limits the number of available stars to constrain the model, thus favouring simpler models. Then, these simple piecewise models defined in each CCD cannot correctly model spatial variations covering the entire focal plane. As a consequence, PSF modelling errors arise. To tackle both problems simultaneously, a new PSF model coined MCCD [3] was recently proposed. MCCD can model the full focal plane and that considers both types of variations. It can successfully include the camera geometry in the PSF model. MCCD is based on a matrix factorisation scheme that uses different mathematical tools, such as sparse regularisation for PSF denoising and graph theory to handle localised spatial variations, among others. The training algorithm combines the previous concepts with block coordinate descent, efficient convex optimization methods and proximal algorithms.

**Goals.** One of the most significant limitations of ground-based PSF models is that the fast-changing and stochastic atmosphere limits the number of stars available to constrain the model. As a consequence, PSF models are built independently for each camera exposure. However, the different survey data releases are done in batches as the sky coverage increases. Once a good part of the survey area has been imaged, one can compute the average ellipticity of the observed stars as a function of their position on the focal plane. The atmospheric ellipticity contribution to the star observations has a zero mean. Therefore, we can obtain a fine-sampled characterisation of the ellipticity contribution of the telescope's optical system. At the time of writing, no PSF model is currently exploiting this information. A single exposure does not allow for recovering the high-frequency variations due to the lack of constraining information on the available stars.

We propose to build a data-driven prior of the telescope's optical aberrations with the help of deep learning techniques. The prior will be incorporated into the PSF model by exploiting recent plug-and-play approaches [4]. We have created a set of realistic simulations based on the measurements of $10^7$ stars from the Canada-France-Hawaii Telescope (CFHT). We plan to use the simulations to train deep learning-based denoisers. These networks can then be included as proximal operators in the optimisation framework of the MCCD PSF model

[3]. The way the denoisers are included follows the plug-and-play approach, which avoids the dangerous black-box usage of deep neural networks. The framework provides a controlled environment to exploit the power of the deep learning-based denoisers.

Once the new model has been validated with simulations, the goal is to demonstrate its performance with real observations from the ground-space survey Canada-France Imaging Survey (CFIS) at the CFHT. To accomplish this task we will make use of the shape measurement pipeline, ShapePipe [5], which already incorporates the MCCD PSF model.

## The candidate

The candidate must be pursuing a Master 2 degree (or equivalent) and should have a background in signal/image processing. The candidate should be comfortable with the Python programming language, and ideally with a deep learning framework (e.g. TensorFlow, PyTorch, JAX) and open-source and collaborative development tools (e.g. GitHub). Knowledge of machine learning and experience processing astronomical images is not required but is beneficial.

The candidate will acquire expertise in sparse image processing, convex optimisation techniques, machine learning and deep learning. In addition, the intern will learn to work in a collaborative development environment and contribute to existing software packages. The knowledge acquired during the internship applies to a wide range of applications in various fields, e.g., biomedical imaging, and astrophysics.

## Contact

The internship will take place in the LILAS lab (CEA Saclay), which is working on signal (and image) processing and machine learning applied to physics applications.

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- Lab: IRFU institute at the CEA Saclay centre,
- Application deadline: 1st of March 2024.

## References


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