PhD project (2026-2029): Point Spread Function Modelling for Space Telescopes with a Differentiable Optical Model

Keywords: *Machine learning, Inverse problems in imaging, Instrumental response modelling*

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 instrumental response of the telescope, called the 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 [2]. The PSF field can be interpreted as a convolutional kernel that affects each of our observations of interest, which varies spatially, spectrally, and temporally. The PSF model needs to be able to cope with each of these variations. We use specific stars considered 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 degradations depending on the properties of the telescope. These degradations include undersampling, integration over the instrument 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 [3] for a recent review on PSF modelling.

The recently launched *Euclid* survey represents one of the most complex challenges for PSF modelling. Because of the very broad passband of *Euclid*'s visible imager (VIS) ranging from 550nm to 900nm, PSF models need to capture not only the PSF field spatial variations but also its chromatic variations. Each star observation is integrated with the object's spectral energy distribution (SED) over the whole VIS passband. As the observations are undersampled, a super-resolution step is also required. A recent model coined WaveDiff [4] was proposed to tackle the PSF modelling problem for *Euclid* and is based on a differentiable optical model. WaveDiff achieved state-of-the-art performance and is currently being tested with recent observations from the *Euclid* survey.

The James Webb Space Telescope (JWST) was recently launched and is producing outstanding observations. The COSMOS-Web collaboration [5] is a wide-field JWST treasury program that maps a contiguous 0.6 deg^2 field. The COSMOS-Web observations are available and provide a unique opportunity to test and develop a precise PSF model for JWST. In this context, several science cases, on top of weak gravitational lensing studies, can vastly profit from a precise PSF model. For example, strong gravitational lensing [6], where the PSF plays a crucial role in reconstruction, and exoplanet imaging [7], where the PSF speckles can mimic the appearance of exoplanets, therefore subtracting an accurate and precise PSF model is essential to improve the imaging and detection of exoplanets.

PhD project

The candidate will aim to **develop more accurate and performant PSF models for space-based telescopes exploiting a differentiable optical framework** and focus the effort on *Euclid* and JWST.

The WaveDiff model is based on the wavefront space and does not consider pixel-based or detector-level effects. These pixel errors cannot be modelled accurately in the wavefront as they naturally arise directly on the detectors and are unrelated to the telescope's optic aberrations. Therefore, as a first direction, we will **extend the PSF modelling approach, considering the detector-level effect by combining a parametric and data-driven (learned) approach**. We will exploit the automatic differentiation capabilities of **machine learning frameworks** (e.g. TensorFlow, Pytorch, JAX) of the WaveDiff PSF model to accomplish the objective.

As a second direction, we will consider the **joint estimation of the PSF field and the stellar Spectral**

Energy Densities (SEDs) by exploiting repeated exposures or dithers. The goal is to improve and calibrate the original SED estimation by exploiting the PSF modelling information. We will rely on our PSF model, and repeated observations of the same object will change the star image (as it is imaged on different focal plane positions) but will share the same SEDs.

Another direction will be to **extend WaveDiff for more general astronomical observatories like JWST** with smaller fields of view. We will need to constrain the PSF model with observations from several bands to build a unique PSF model constrained by more information. The objective is to develop the next PSF model for JWST that is available for widespread use, which we will validate with the available real data from the COSMOS-Web JWST program.

The following direction will be to extend the performance of WaveDiff by including a continuous field in the form of an **implicit neural representations** [8], or **neural fields (NeRF)** [9], to address the spatial variations of the PSF in the wavefront space with a more powerful and flexible model.

Finally, throughout the PhD, the candidate will **collaborate on *Euclid's* data-driven PSF modelling effort**, which consists of applying WaveDiff to real *Euclid* data, and the **COSMOS-Web collaboration to exploit JWST observations**.

The applicant profile

The successful candidate should have an M2 master or an engineering diploma degree, with a specialisation on signal processing/statistics/machine learning or astrophysics. Basic knowledge of statistical inference, signal processing, and machine learning is expected. The candidate should be comfortable with software development (at least in Python) and, ideally, be familiar with a deep learning framework (e.g. TensorFlow, PyTorch, JAX). Experience with open-source and collaborative development tools (e.g. GitHub) is desirable. The research team is international, so speaking French is not a requirement.

Collaborations

The candidate will be a member of the *Euclid* consortium and participate in the data-driven PSF modelling effort.

Scientific environment

The successful candidate will be based in the ALEPH group from the DEDIP department of the IRFU institute from the CEA Paris-Saclay research centre which is located 20km south of central Paris in the Paris-Saclay cluster. The PhD supervision will be assured by Dr. Tobías I. Liaudat and Dr. Jérôme Bobin. The ALPEH group focuses on signal (and image) processing and machine learning applied to astrophysics applications including gravitational wave data analysis and radio interferometric imaging. The candidate will be able to benefit from the expertise of the growing machine learning and artificial intelligence community on the Saclay plateau. We expect strong interactions with the PSF team at the CosmoStat laboratory, which has a long tradition of developing cutting-edge statistical tools for the analysis of astronomical and cosmological data and is heavily involved in several projects including the ESA *Euclid* space telescope.

Computational resources The successful candidate will have access to the Jean Zay supercomputer, largest GPU cluster for research in France (which has recently been upgraded with 1400 H100 GPUs), as well as the IRFU's CPU cluster. Most of the development will rely on GPUs.

Contact

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The deadline for applications is the 1st April 2026.

Application Please send an application by email with a subject starting with [PhD-PSF] to tobias.liaudat@cea.fr and jerome.bobin@cea.fr, including: a CV, a transcript of grades, and the names and addresses of at least one reference (max. 2), which will be later asked for a recommendation letter.

References

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