Centre de Calcul
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Study and optimization of PSF processing for the ZTF experiment

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Overview

- **Introduction**
  - Cosmology and the Zwicky Transient Facility
  - Measurement and image calibration pipeline
- **Optimization of the PSF computation**
  - Models
  - IT infrastructures
  - Optimizers and data processing
- **Results**
  - Gaussian model
  - Moffat model
- **Conclusions and perspectives**

Introduction

Cosmology

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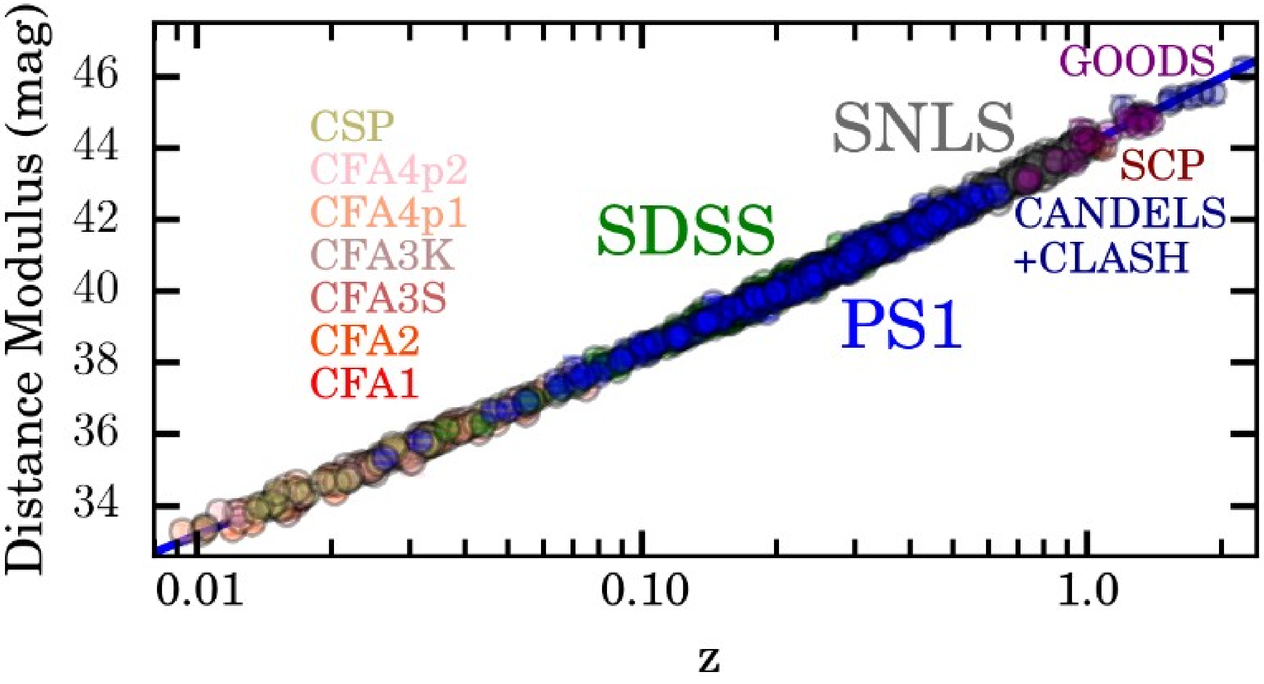


Study of Type Ia Supernovae (SNeIa) in order to understand the acceleration of the expansion of the universe

SNeIa are standard candles (fixed luminosity L)

$$F = L / 4 \pi d^2$$

The Zwicky Transient Facility

The detector:

- Palomar Mountain, California (USA), inaugurated in March 2018

- Collaboration: US National Science Foundation
  & universities and institutes of Europe and Asia

- Scan the Milky Way plane twice a night and scan the entire northern sky in 3 night

- Composed by 16 CCD (Charge-Coupled Devices),
  i.e. 64 quadrants

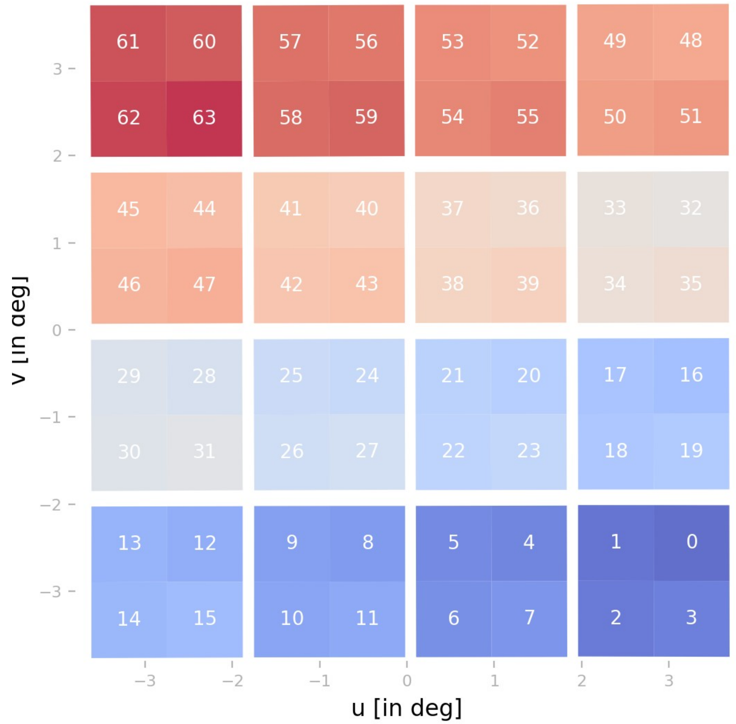
The CCD:

- Sensors that detect the photons

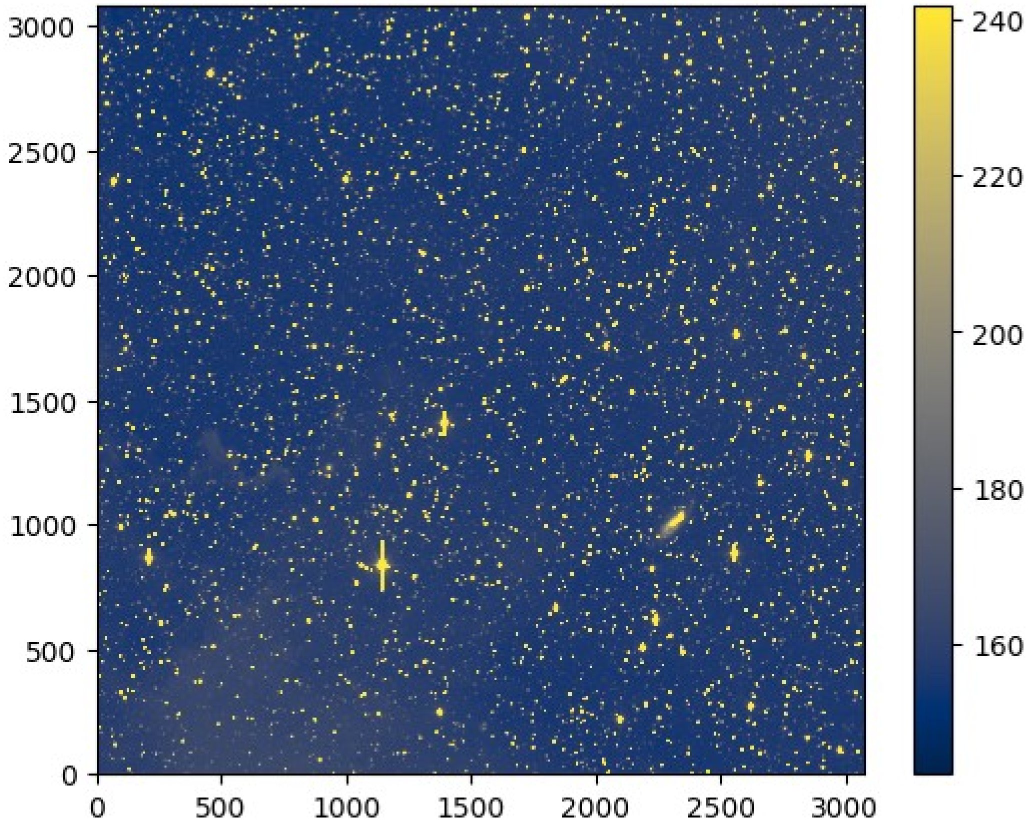
- Photons excite electrons in the CCD pixels,
  conversion in electrical charge,
  then in digital signal (ADU process)

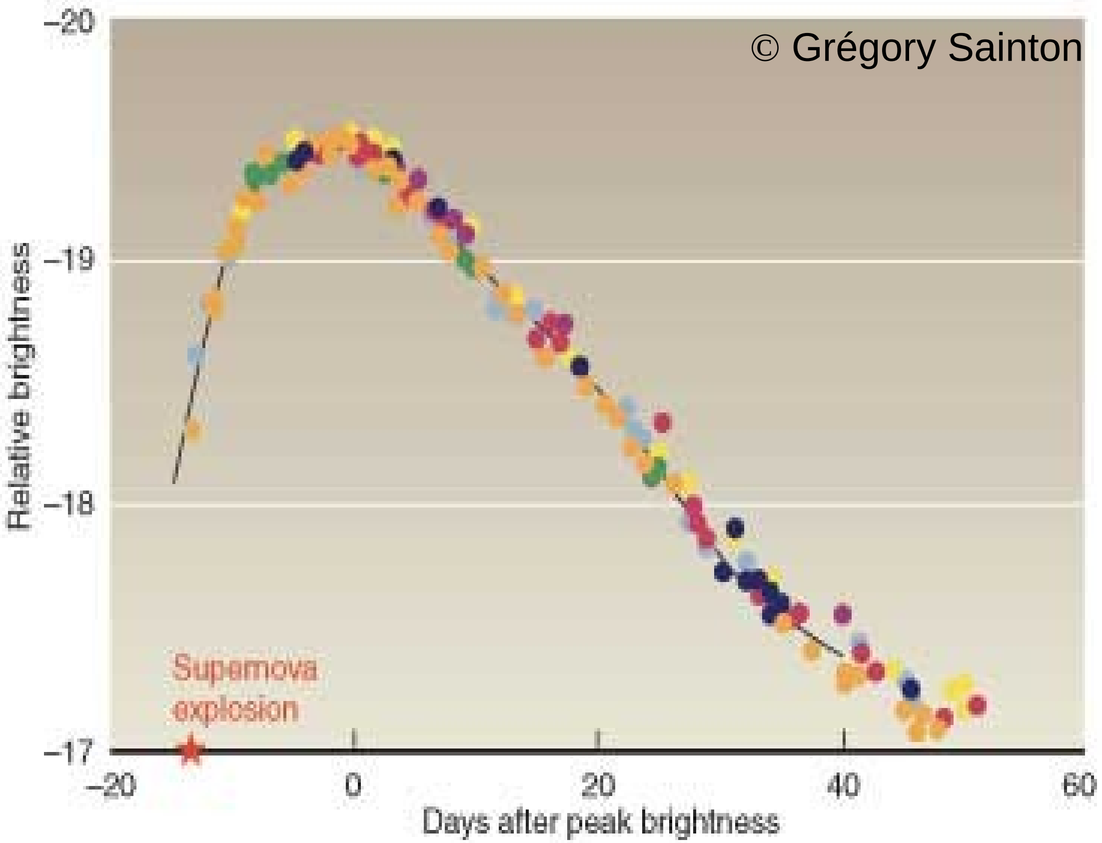
- Raw image acquisition

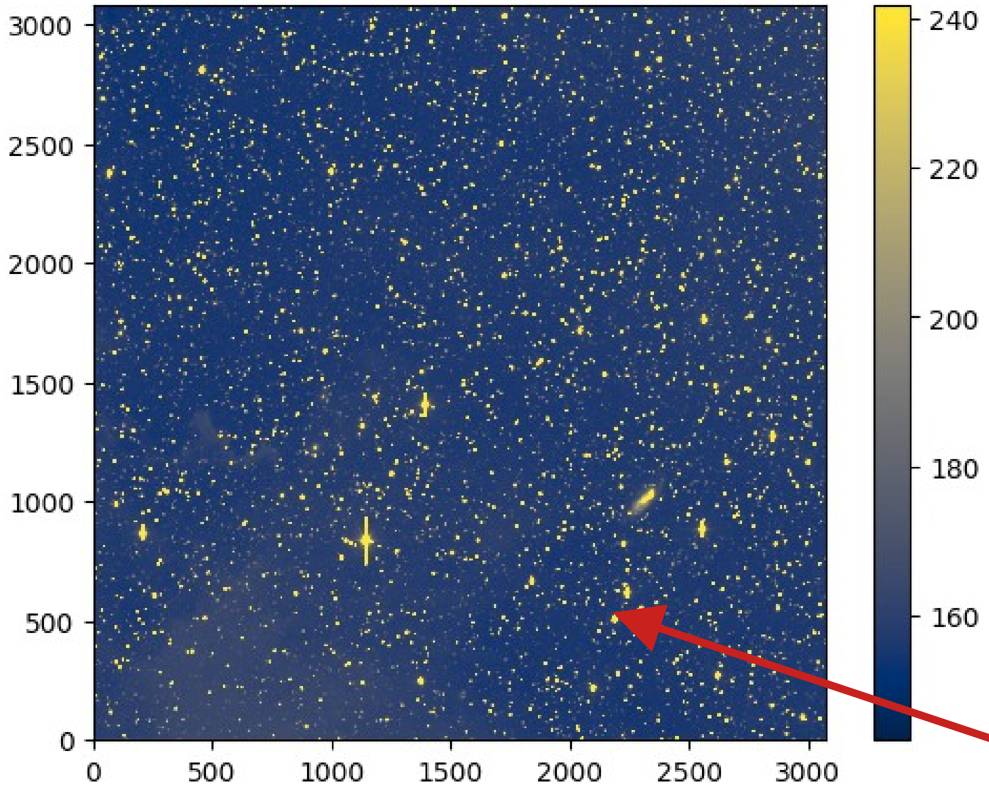
- Calibration of raw images to obtain scientific images



Measuring photometric luminosity



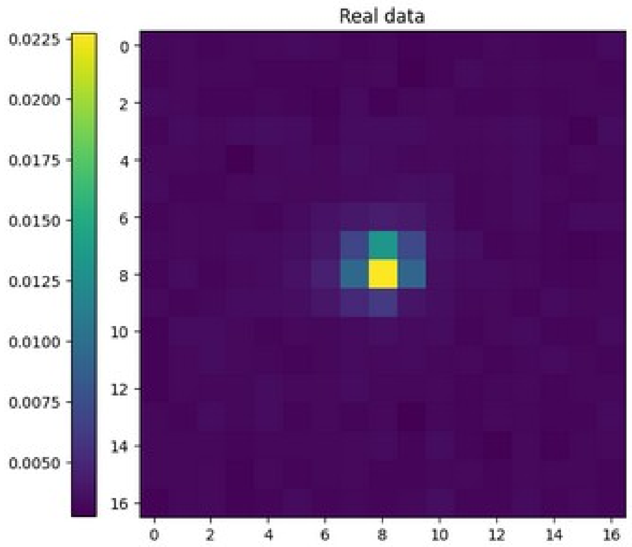




→ Master-bias (~ ms)

→ Master-flat (~ ms)

→ Flux Extraction (~ 10s)



X ~ 20 000

X 50 000 000 images

Computing center (Lyon)

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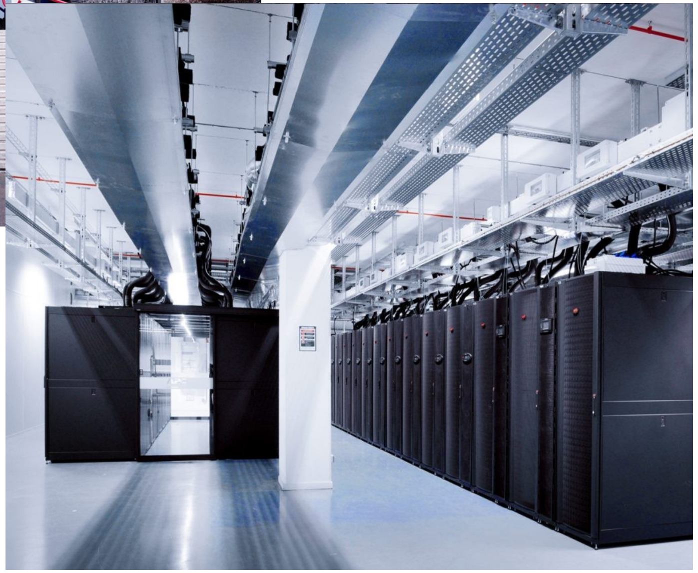
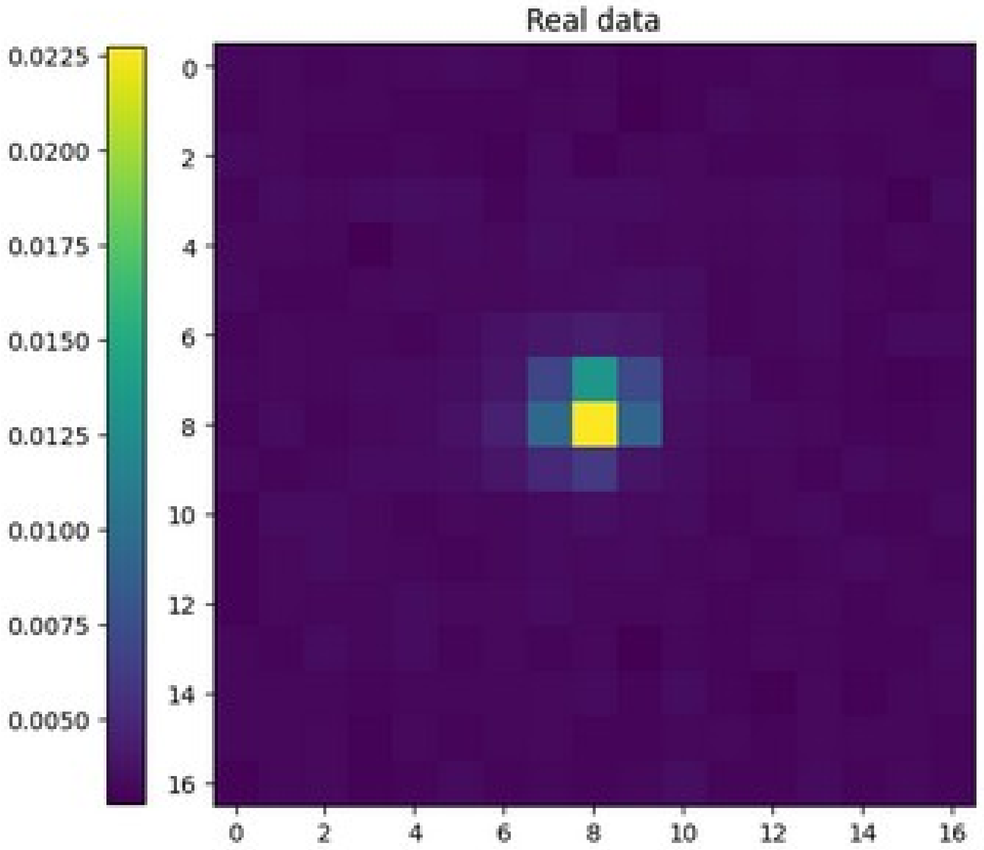


- Located at Lyon
- 1700 m² over two computer rooms
- ~850 servers
- ~60 GPU and ~20 000 CPU

Optimization of the PSF computation

Point Spread Function

- Models the spread of light intensity from a point source over an image
- Uses a mathematical function (ideal case: a Dirac peak)
- Point source actually spread over several pixels:
  - Atmospheric effects
  - Defects in the optical instrument
  - Mirror curvature



Models

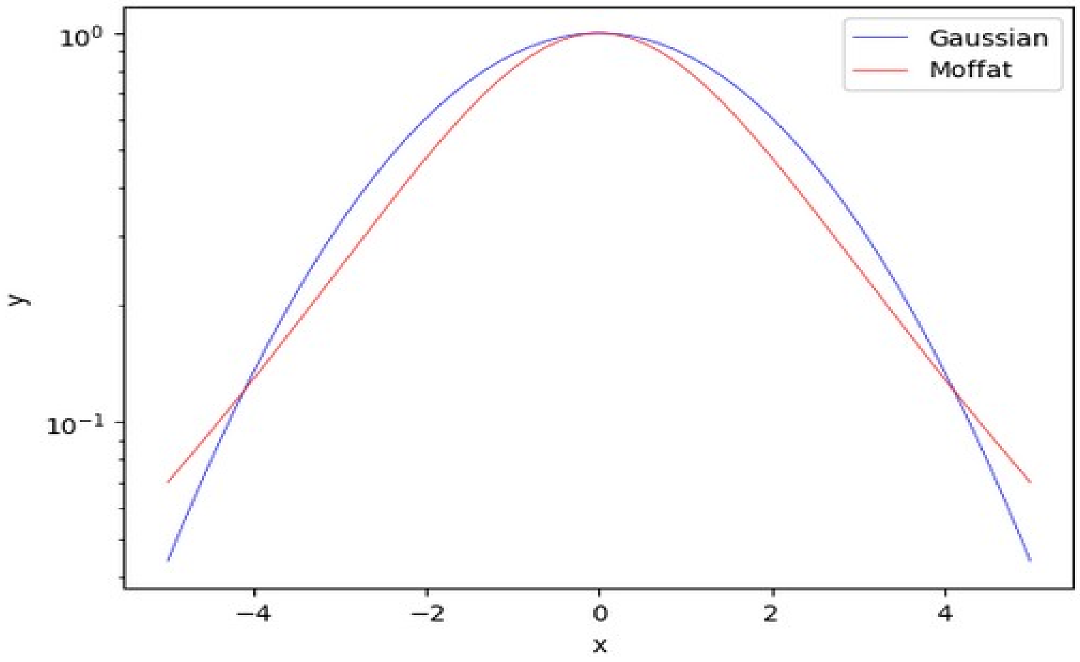
Gaussian distribution: First approach

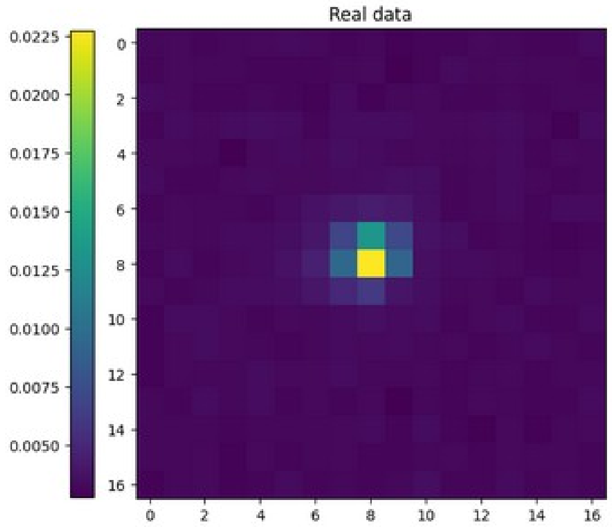
$$f(x) = A \exp\left[-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right] \quad \text{with} \quad A = \frac{1}{\sqrt{2\pi \det(\Sigma)}}$$

Moffat distribution: better point spread model

$$f(x,y,\alpha,\gamma) = A\left[1+\left(\frac{(x-x_0)^2+(y-y_0)^2}{\gamma^2}\right)\right]^{-\alpha} \quad \text{with} \quad A = \frac{\alpha-1}{\pi\gamma^2}$$

Moffat + pixel grid: next step

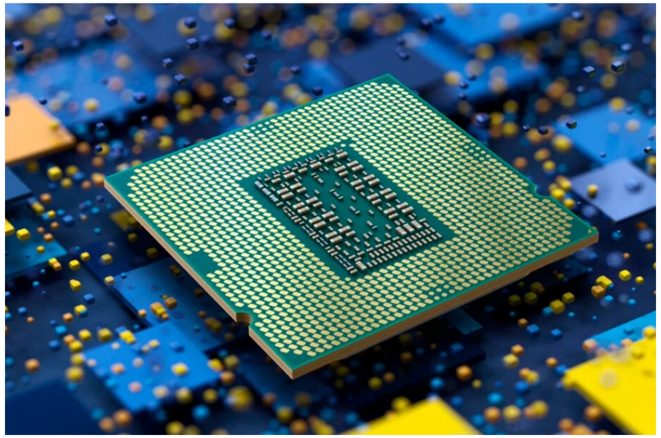




Processing unit architectures

Central processing unit (CPU):

- Electronic chip that carries out computation, data processing and control tasks
- Perform complex operations in single step



Graphics processing unit (GPU):

- Type of processor to manage and speed up graphics
- Perform many simple operations in parallel

Why is a good idea to run the PSF code on GPU?

The PSF code consists mainly of image processing and more specifically pixel by pixel processing

Optimizers

On CPU:

- *scipy.optimize.minimize*

Iterative method to construct an approximation of the Hessian matrix

On GPU:

- *optax.adam*

Gradient based optimization algorithm

```
def fit_adam(func, init_params,
             learning_rate=5e-3, niter=200,
             tol=1e-3,
             **kwargs):
```

- *Truncated Newton Conjugate Gradient (TN-CG)*

Second order optimization algorithm
(takes advantages of the function's curvature)

```
def fit_tncg(func, init_param,
             niter=10, tol=5e-3,
             lmbda=1e2,
             **kwargs):
```

GPU Software framework

Requirements:

- Easy-to-use language to implement in existing official code
- Ability to switch between CPU and GPU depending on machine availability

Available frameworks:

- TensorFlow (developed by Google Brain in 2015)
- PyTorch (developed by Facebook AI Research in 2017)
- JAX (developed by Google Research in 2018)

JAX framework:

Advantages:

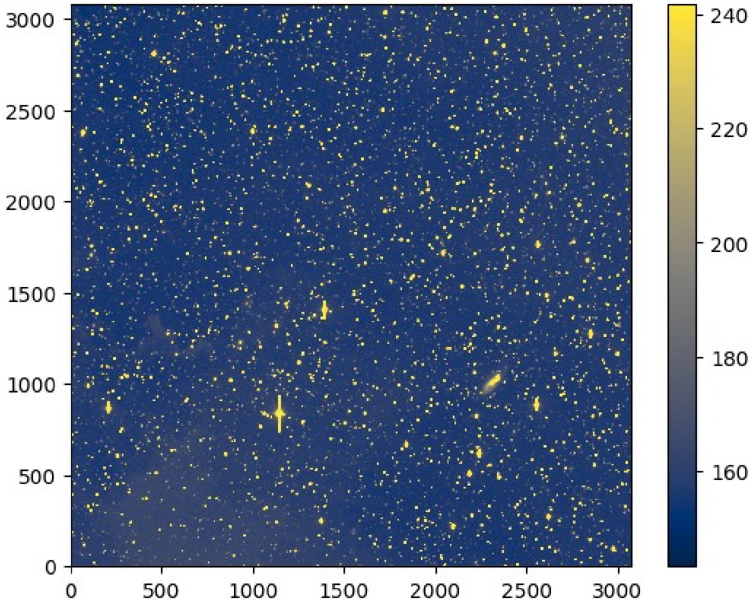
- NumPy-like and SciPy-like
- Uses Autograd (for automatic gradient computation) as TensorFlow and XLA (for optimization and acceleration of computation) as Pytorch

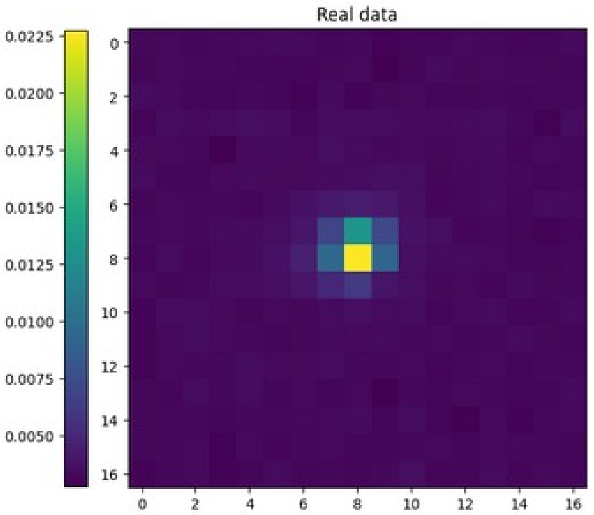
Disadvantages:

- Currently in full development (version 0.4.28, last release in May 2024)
- Lot of changes from one version to the next: older versions not documented

Working environment:

- Python environment on top of the official ZTF environment
- GPU used: NVIDIA V100, 5120 cores, CUDA 12.2
- JAX version used: 0.4.26 (released in April 2024)





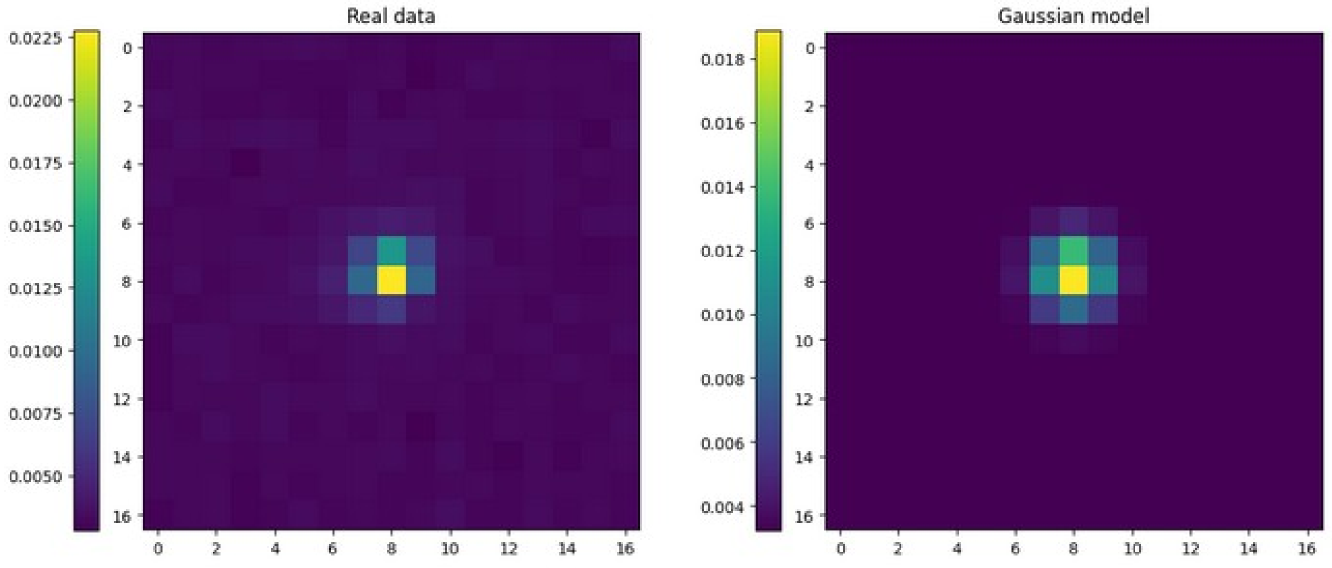
Data processing:

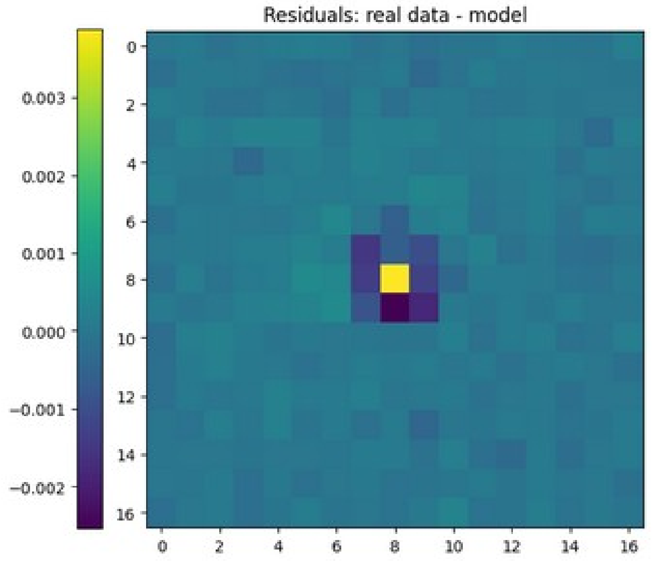
- Creation of stamp for each isolated stars (20arcsec)
- Stars within 15 pixels from the edge are ignored
- 14 < magnitude < 18

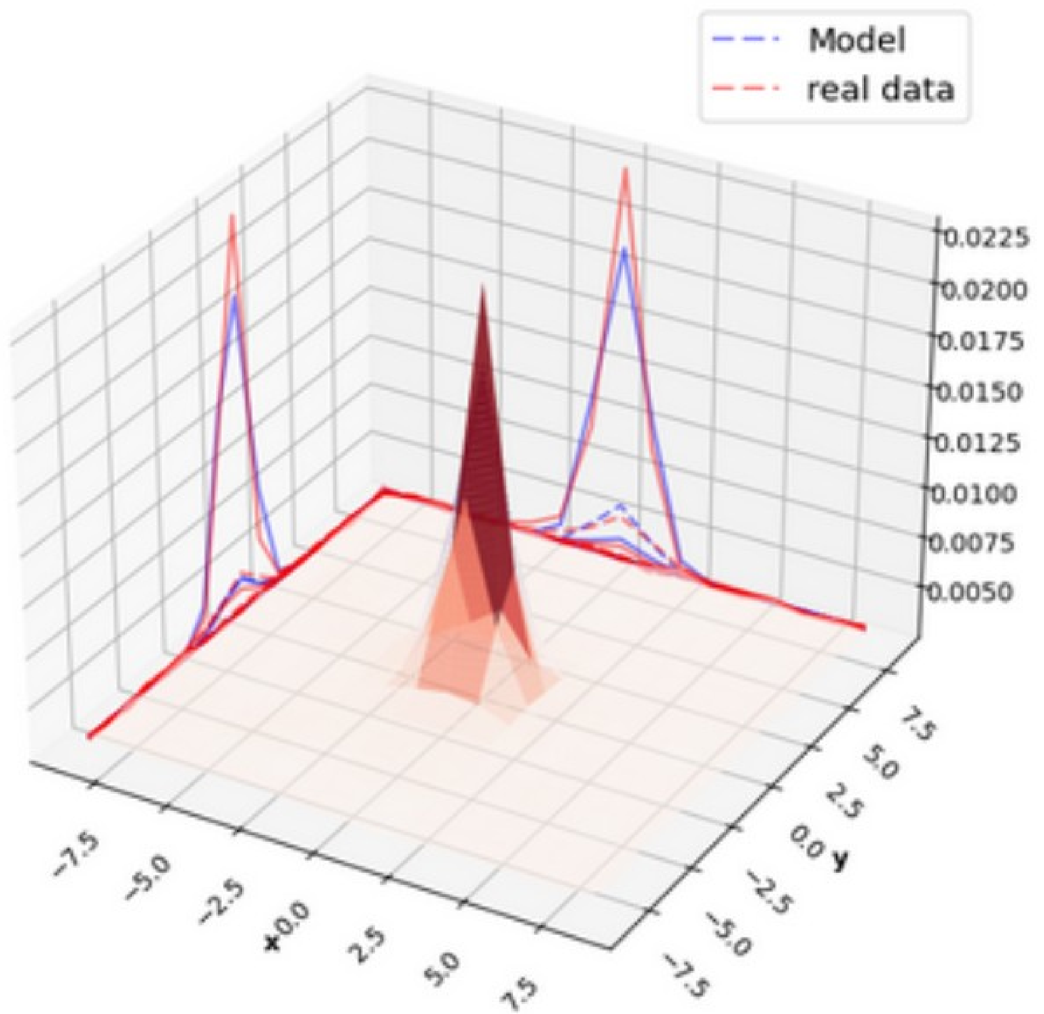
→ At the end: 473 stars are left (15174 stars at the beginning)

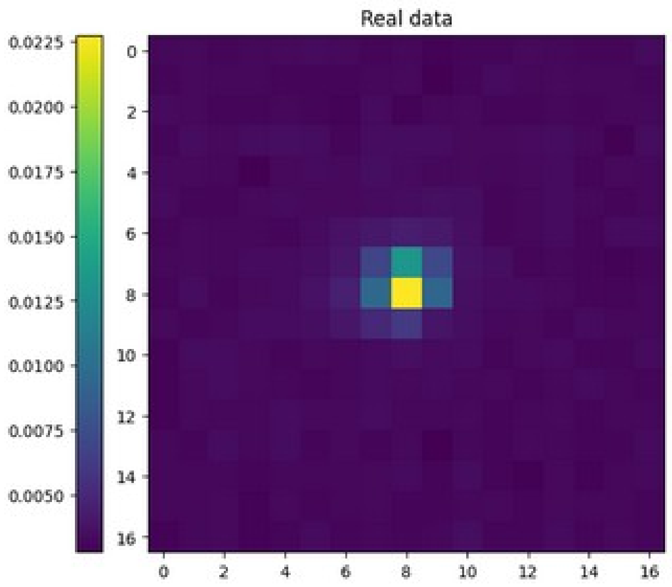
Results

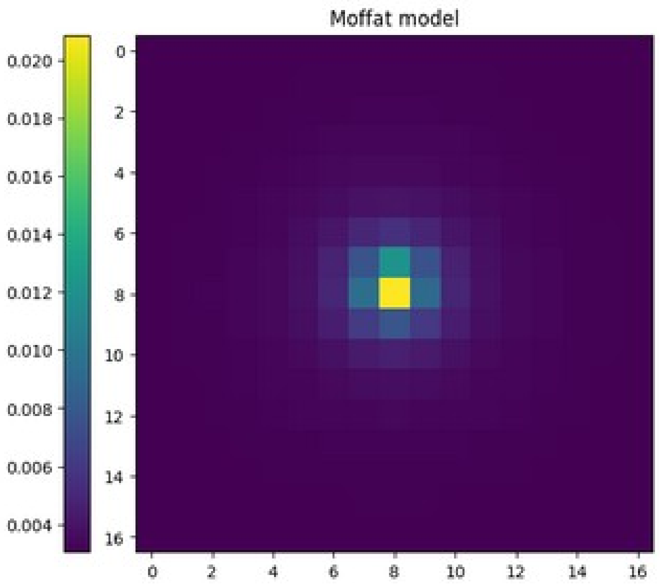
Gaussian model

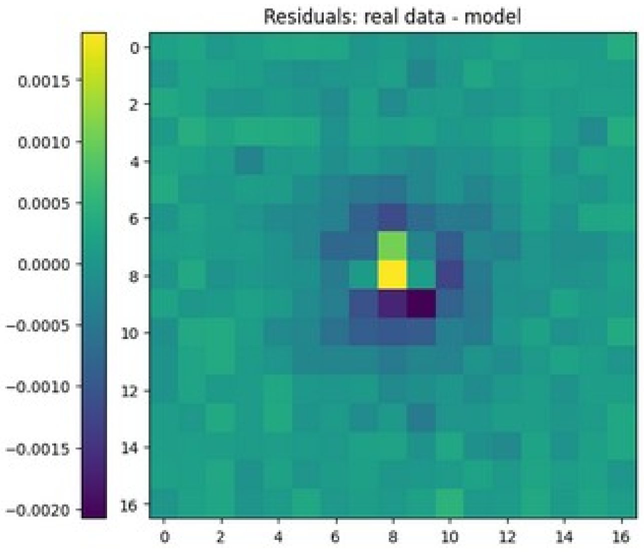


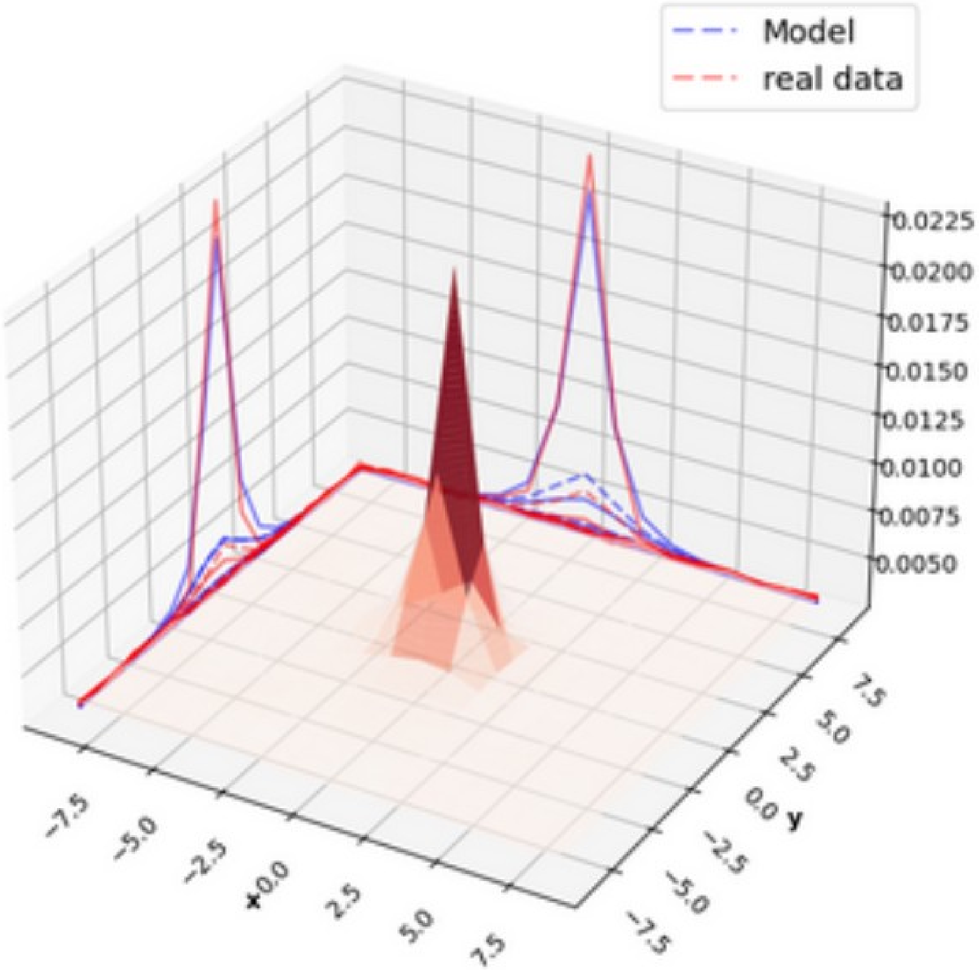




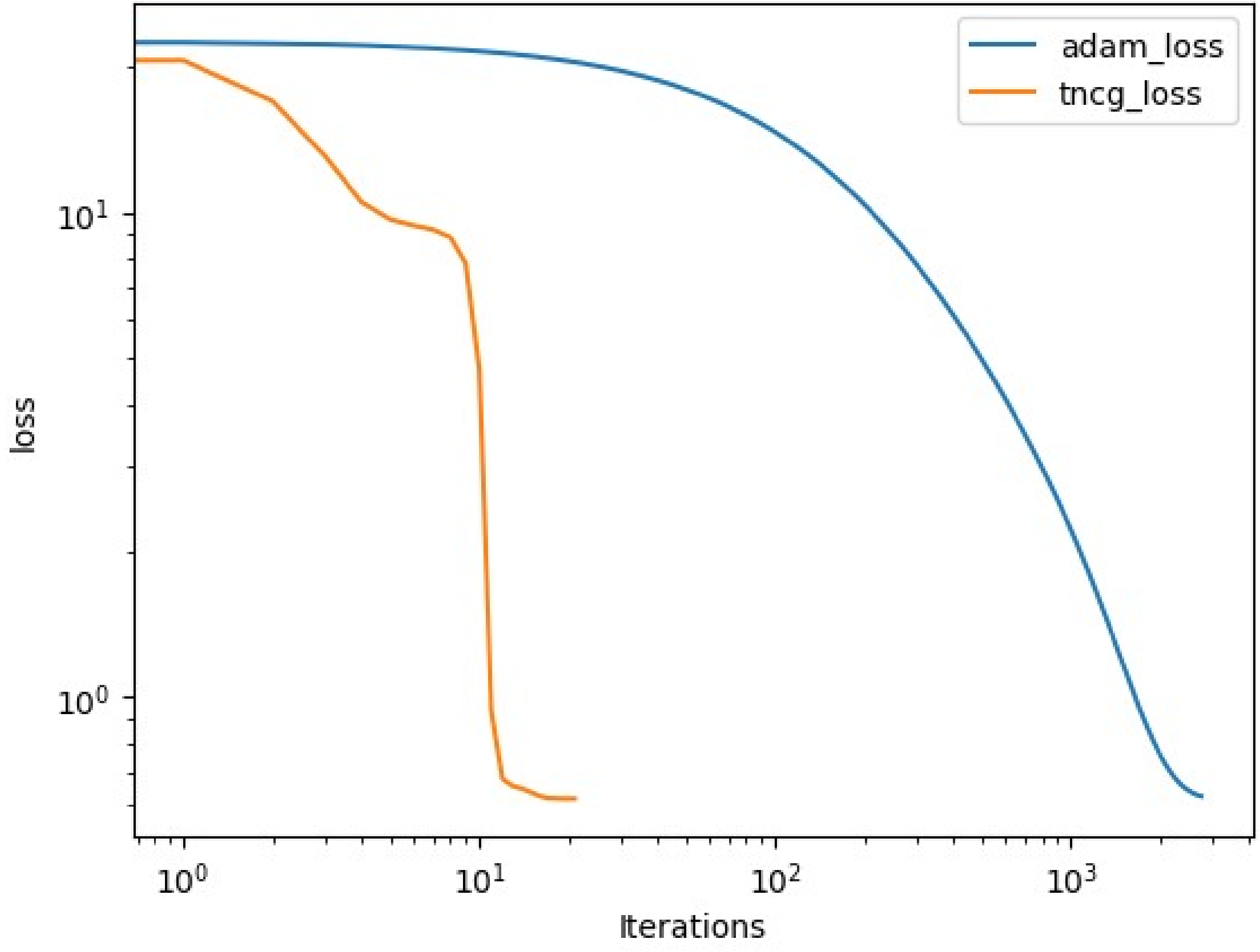

Real data


Moffat model


Residuals: real data - model


Model
real data
y

Loss functions with Gaussian model



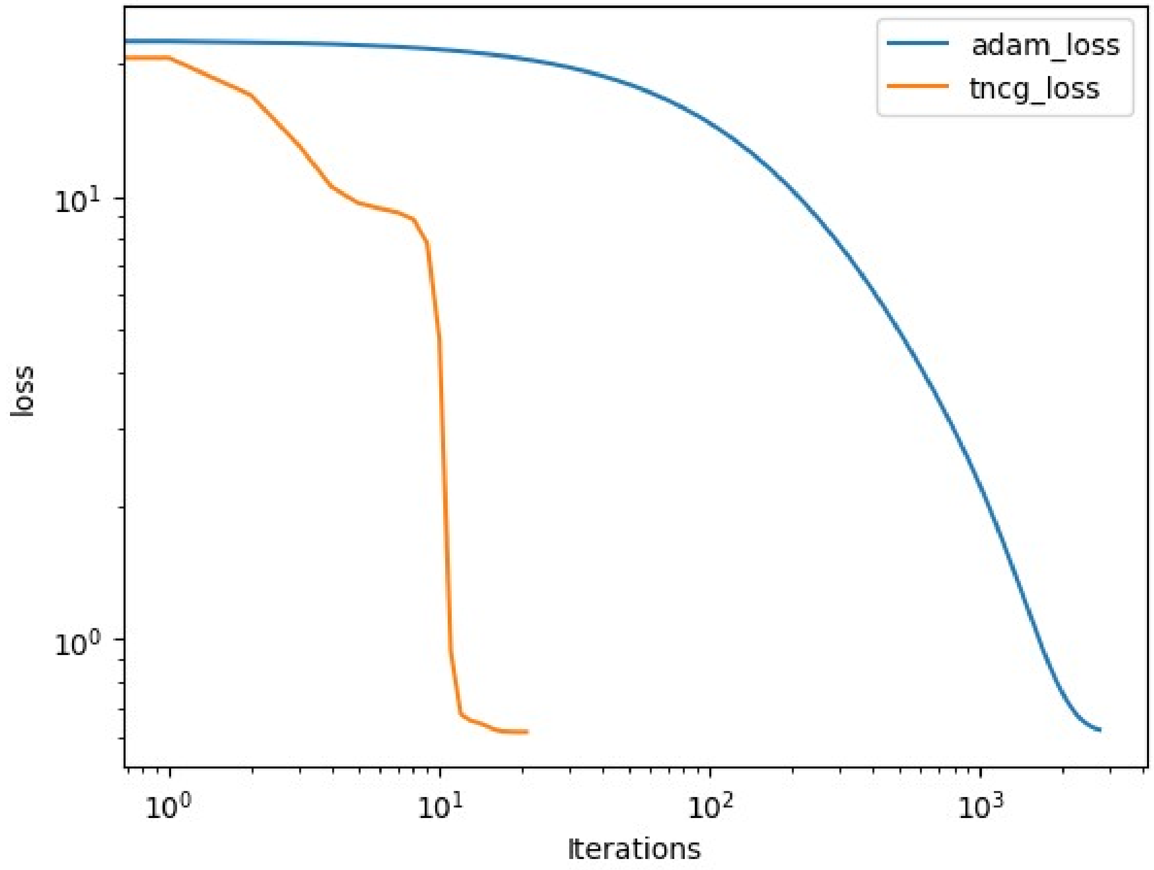
Quantitative measure of the difference between model and real data

- Adam: execution time = 21.7s
  500 iterations
  0.00434s by iteration

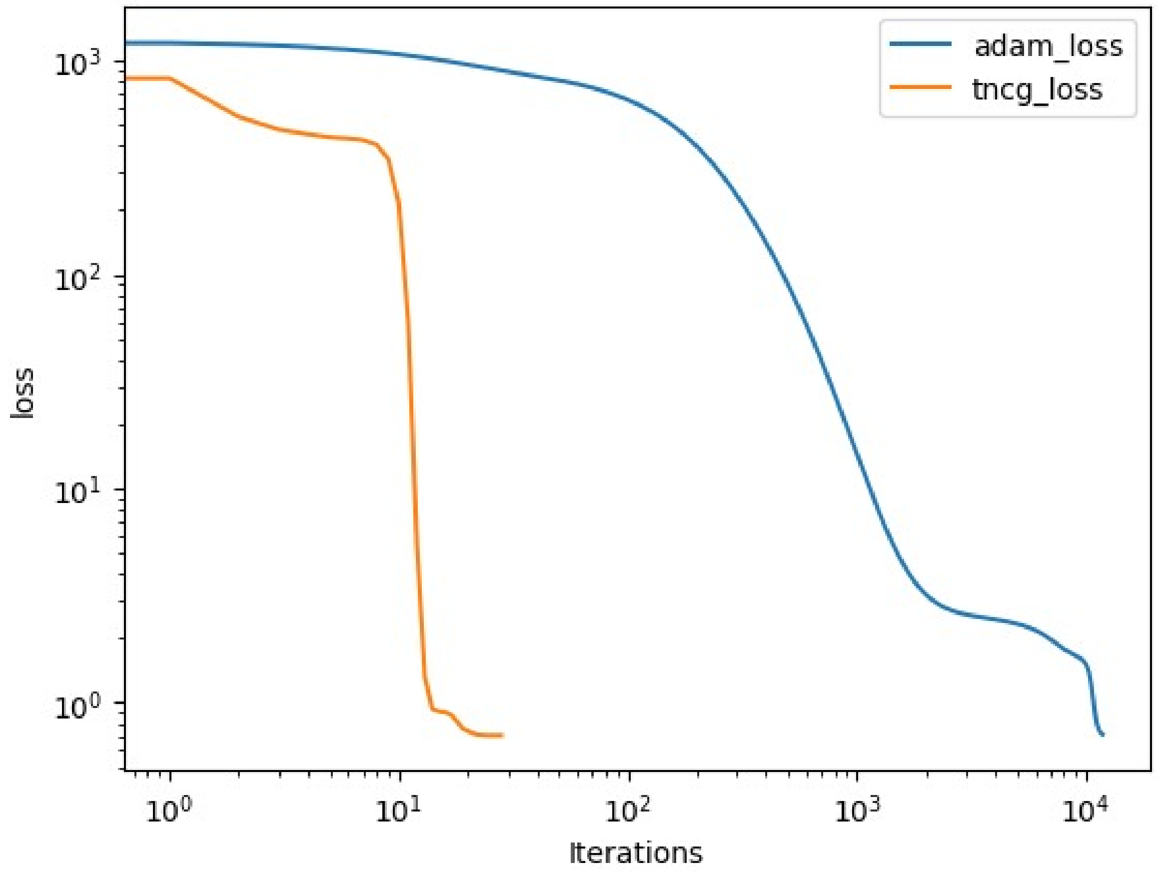
- TN-CG: execution time = 5.39s
  50 iterations
  0.10789s by iteration

Loss functions

Gaussian model

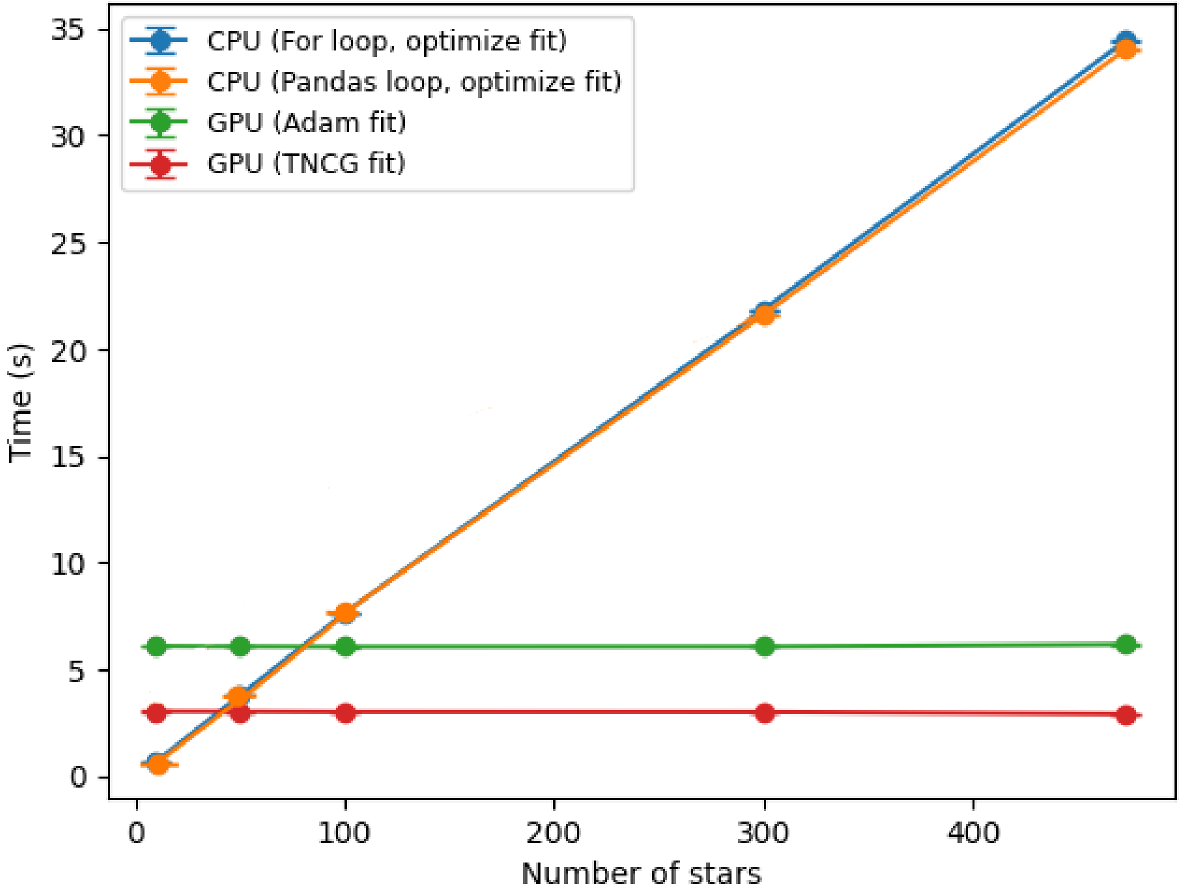


Moffat model

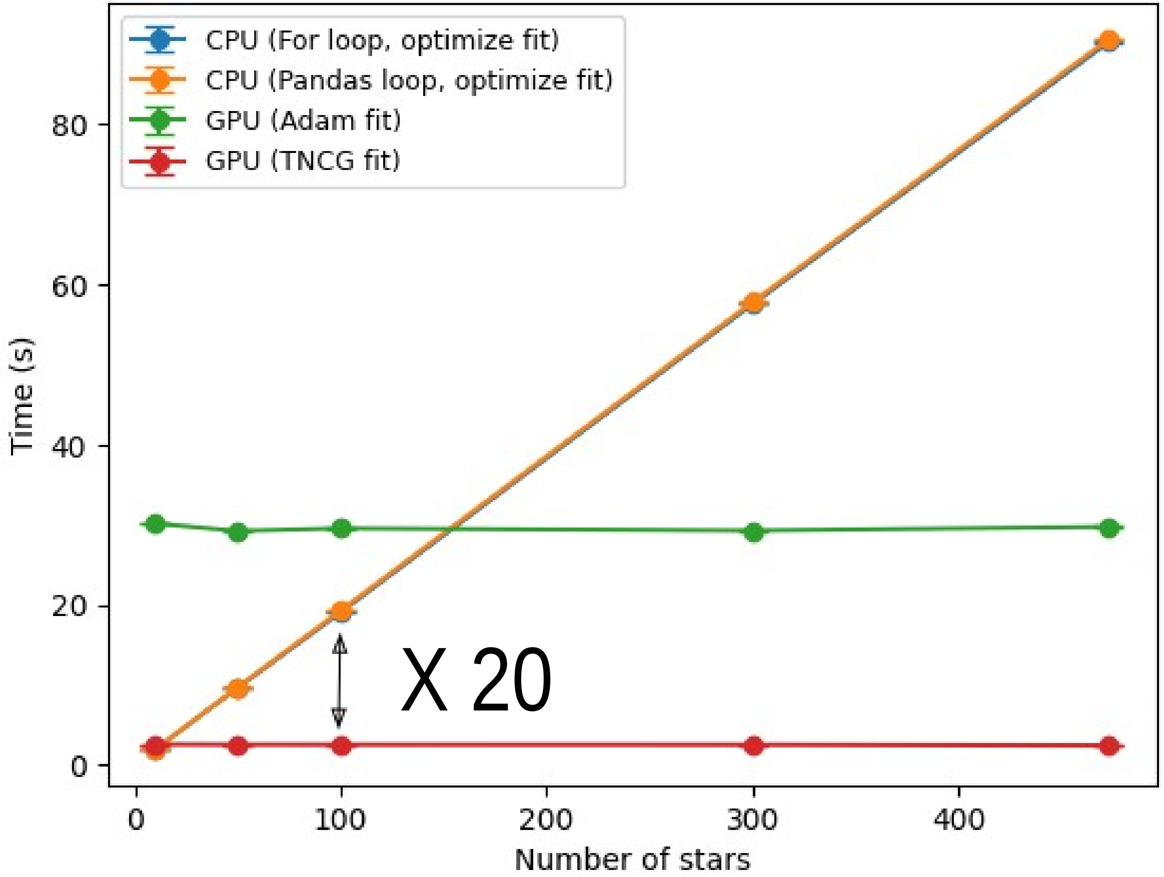


Execution speed

Gaussian model



Moffat model



Conclusions

Conclusions

- The aim of my internship was to find a way of optimizing the PSF code for the ZTF environment
- Started by testing my code on CPU then parallelized on GPU
- Obtain a factor of 20 in execution time between CPU and GPU for 100 stars
- JAX is an adapted framework because it is a NumPy-like code and can run on both CPU and GPU
- Pipeline flexible: use Autograd to automatically compute gradient

Perspectives

For the next month:

- Check the error calculation of the optimized parameters on CPU with the Gaussian and Moffat models
- Do the error calculation with Adam and TN-CG optimizer with JAX
- Compare the testing and training functions with respect to the loss function on GPU
- Add another parameter in the Moffat fit: the pixelgrid
- Run my code on the whole image (all 64 quadrants) and for several images
- CPU tests only run on a single core, GPU tests run on various cores

  → Possibility to parallelize on CPU with Dask on Python

On longer term:

- Implement my code in the official ZTF software
- Add a back-end mechanism (JAX, Dask…) to use the most appropriate processing unit GPU or CPU, depending on their availability on the computing infrastructure.

Thank you for your attention

Back-up

```
guess = [mu, A, b, alpha, gamma]
adam_params, adam_loss = fit_adam(get_logprob, guess, learning_rate=1e-3, tol=1e-5, niter=15000)
```

```
guess = [mu, A, b, alpha, gamma]
tncg_params, tncg_loss = fit_tncg(get_logprob, guess, tol=1e-5, niter=50, lmbda=10000)
```

Back-up

Gauss results:

Parameters	Optimized Value (CPU)	Error (CPU)	Optimized Value (GPU: Adam)	Optimized Value (GPU: TN-CG)
x_0	0.47144	0.65313	0.018556	0.016890
y_0	0.24933	0.34438	0.254136	0.247583
A	0.08768	0.05297	0.082898	0.079343
σ_x	0.99996	0.00953	0.914114	0.879041
σ_y	0.99996	0.00948	0.916828	0.882730
b	0.00319	0.00084	0.082898	0.003217
χ^2	7.44529e-05		0.14382	0.10835

Moffat results:

Parameters	Optimized Value (CPU)	Error (CPU)	Optimized Value (GPU: Adam)	Optimized Value (GPU: TN-CG)
x_0	0.48614	0.6460	0.104471	0.019067
y_0	0.27890	0.3563	0.284396	0.248053
A	0.12203	0.0376	0.020781	0.019664
γ	0.99994	0.0100	0.792515	0.843164
α	1.00007	0.0100	1.130729	1.154012
b	0.00280	0.0010	0.003004	0.002990
χ^2	9.85163e-05		0.13909	0.15470

Back-up

Image calibration pipeline:

- Bias adjustment: residuals electrons propagating through pixels and create background noise (temperature effect)
- Overscan: to check how many electrons are beyond the CCD (add of 30 pixels to pixelgrid)
- Brighter-fatter effect: distortion of light source image (too many photons)
- Saturation effect: too many electrons resulting a saturation threshold, making ADU conversion difficult

→ Master-bias (average of 20 sequences)

- Flat correction: each pixel reacts differently to photon stimulation (we want to homogenize) flat screen in front of the telescope sending the same light source to each pixel

→ Master-flat (average of 20 sequences)

- Applying master-bias to master-flat

→ Scientific images