GALMoss: GALaxy Modeling Of Surface brightness fitting via gradient deScent

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Abstract

We introduce **GalMOSS**, a Python-based, torch-powered tool designed for the photometric modelling of galaxy profiles. Leveraging GPU acceleration, **GalMOSS** efficiently addresses the computational demands associated with large-scale galaxy surveys. Our testing on a sample of galaxies from the Sloan Digital Sky Survey (SDSS) showed a high level of agreement with results obtained using GALFIT. We further demonstrate the capabilities of **GalMOSS** by fitting profiles to a dataset of one million galaxies. This task was completed in approximately five hours on a single NVIDIA A100 GPU. The software incorporates a range of widely-used profiles, including Sérsic, broken-exponential, Ferrer, and Moffat. With an architecture prioritizing extensibility, **GalMOSS** simplifies the integration of new models, making it a versatile tool for photometric galaxy profile modeling.

Problems

1. Initial parameters sensitivity

Most of the fitting packages need good initial input, otherwise it cannot fit properly.

2. Numerous amount of data

Large sky servey is very efficient on data production, E.g. LSST could provide 15TB data per night.

3. Limitation of machine learning method

Machine learning method is fast but not physical, besides, their abilities are limited by their training dataset, (e.g. DeepLeGATo can only fit sérsic model).

8,000 galaxies

ONLY 15mins!

FITTING:

1. Quickly 2. User-friendly 3. Parallel

Model

Our fitting model is organized as following.

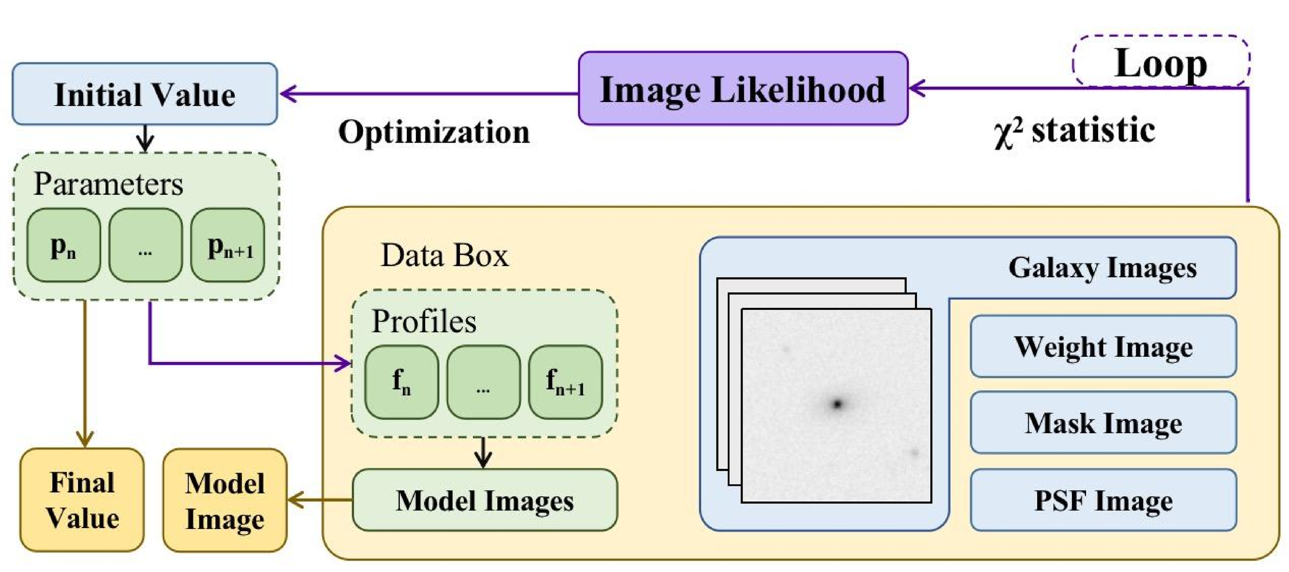

Image likelihood: χ^2 distribution, to evaluate the similarity between model image and raw iamge.

Parameter Optimization: Gradient Descent using back propagation, fastened by **GPU**.

Methodology

Following model image generation, GalMOSS implements an extended chi^2 **likelihood** and **Gradient Descent** optimization, leveraging Python and PyTorch functionalities.

Parameter fitting uncertainty:

· Covariance matrix, bootstrap

Experiment

Our fitting process was executed in a machine with following specifications: CPU-AMD EPYC 7763; GPU-NVIDIA A100 (80G); with environment as following: Python 3.9.13; PyTorch 1.13.0, CUDA 11.6.

Data:

We download 8,291 SDSS galaxy image data belongs to MPP-VAC catalog at size 128*128, which is fitted by GALFIT.

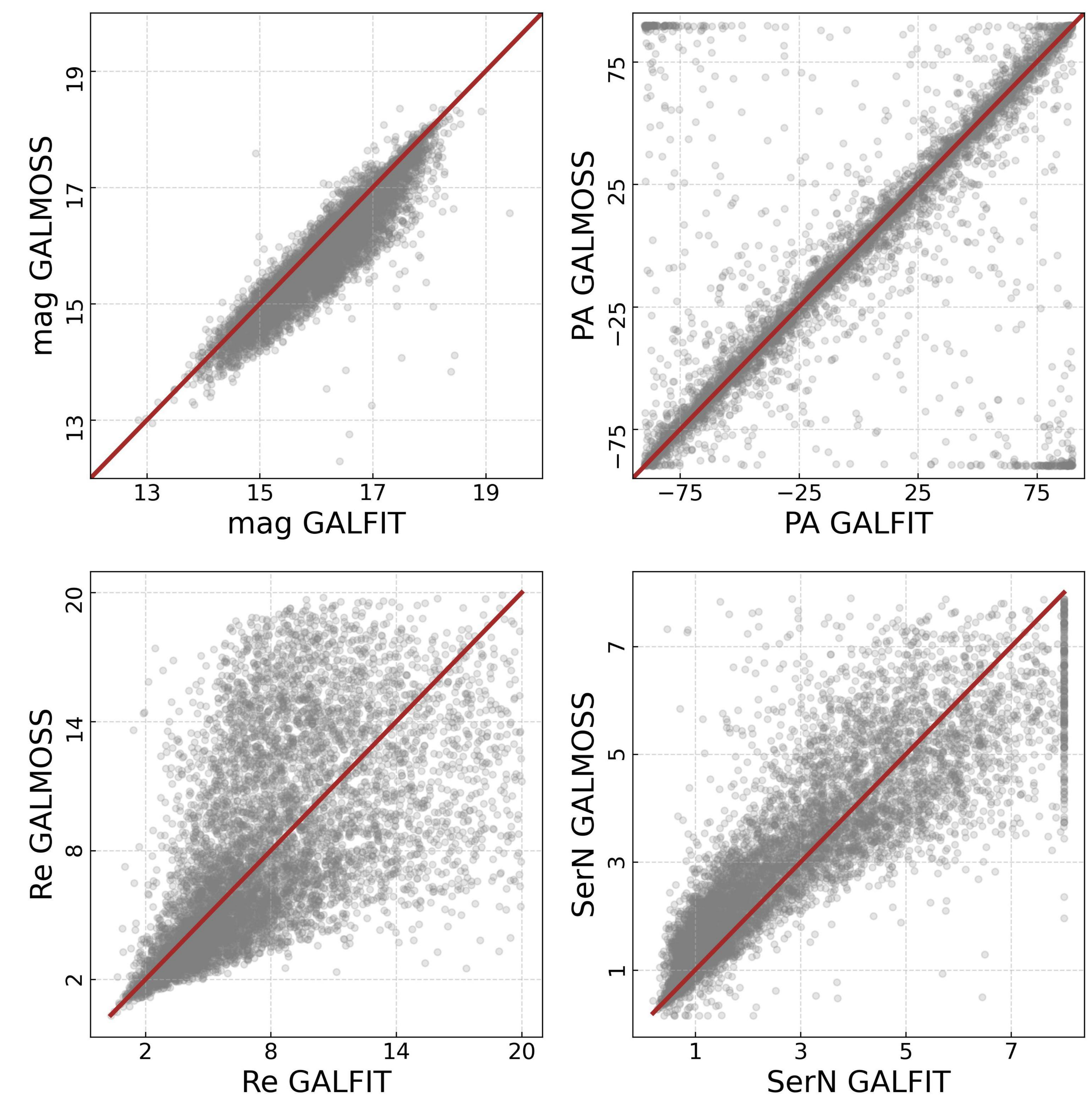

Figure 1: Comparison of fitting result between GALFIT and GALMoss

Fitting process:

We produce scale image and initial parameters with SexTractor. We choose single sersic as fitting profile. During the fitting process, we fit 1,024 galaxies simultaneously and iterate for 1,500 times.

Result:

With the specifications mentioned above, we cost 15 minuets to finish fitting. The comparison of fitting result between GALMoss and GALFIT (MPP-VAC catalog) is showed at Fig 1 as a consultant.

The more detailed images for single galaxy are shown in Figure 3 and 4. Figure 3 is the result image for galaxy J100247.00+042559.8 with a more complicated profiles combination: bulge+disk. From the residual we could see GalMOSS models the brightness distribution quite well. Figure 4 shows the 1-d projection.

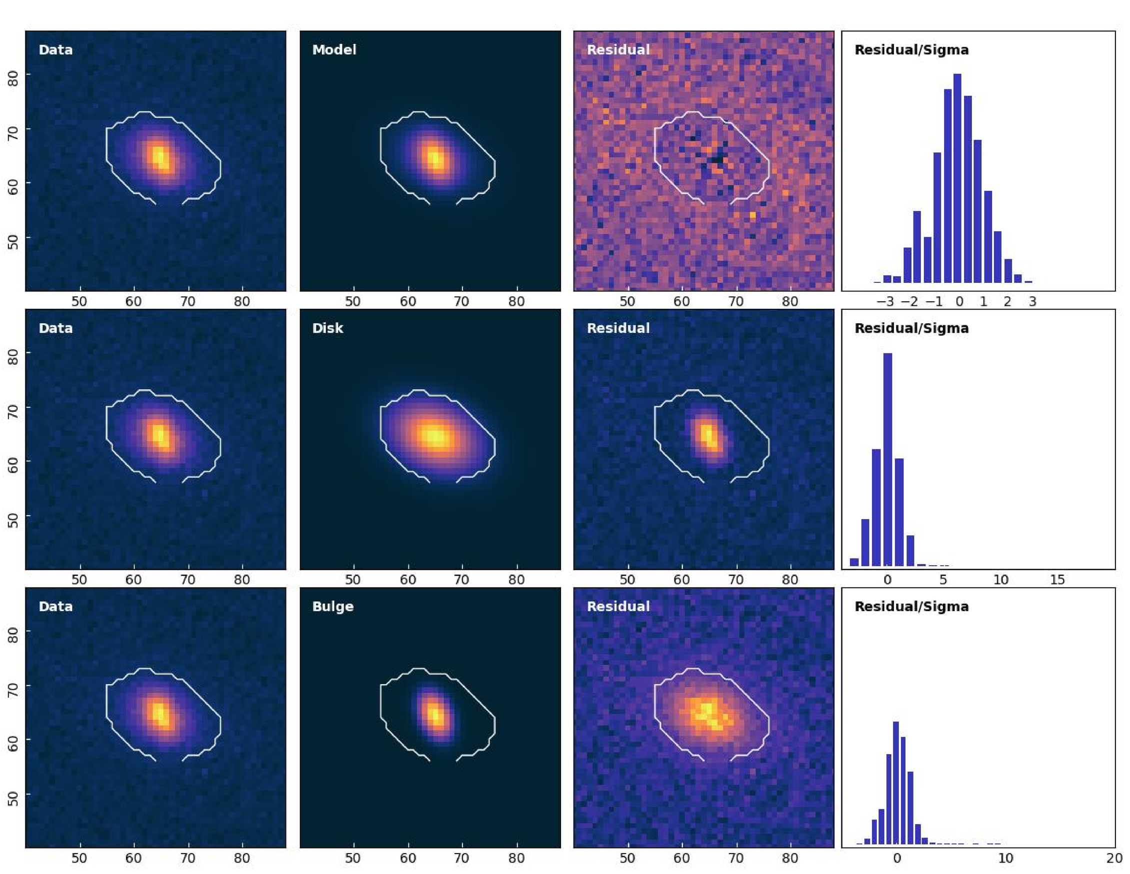

Figure 3: Fitting result of J100247.00+042559.8, the upper panel is the galaxy data, model data and residual data for total model, bulge and disk decomposition.

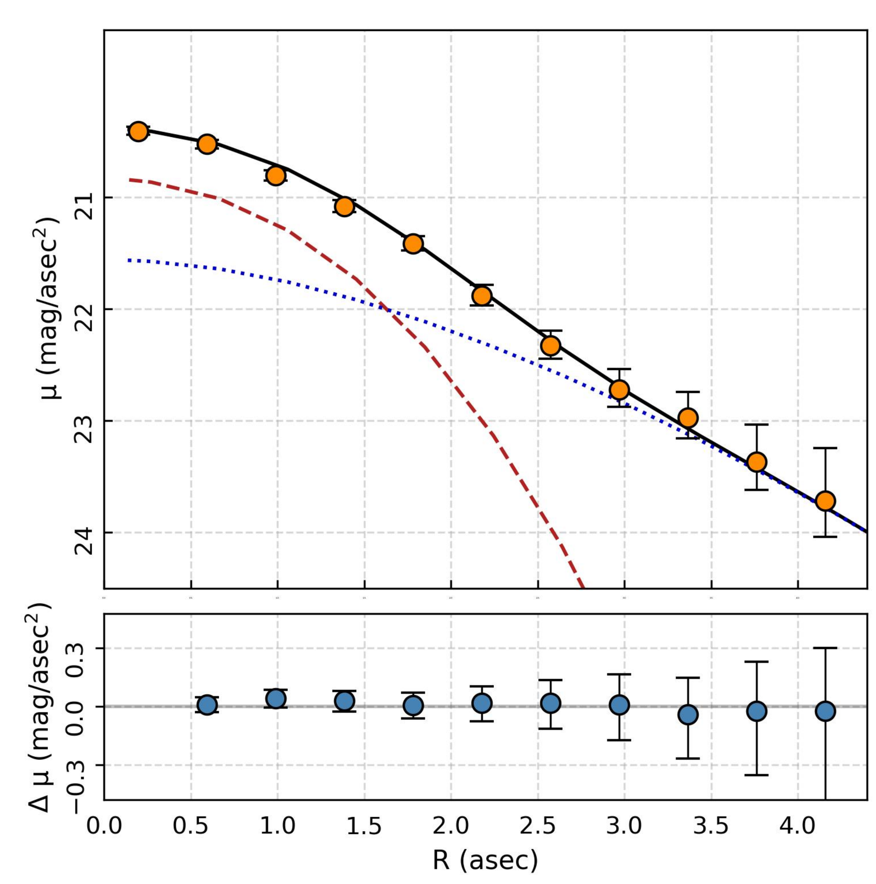

Figure 4: r-band 1-d projection of J100247.00+042559.8. The black line shows the model distribution, and the orange dot with error bar shows the flux distribution of galaxy image with their weight. The red dashed line and blue dot line shows bluge and disk model separately. In the lower panel, the blue dot with error bar shows the flux residual.

Conclusion

Pros:

- Our package could do **parallel** galaxy fitting whitch is unsensitive to initial parameters.
- **"Stepped on"** the fitting process.
- Provide parameter fitting **uncertainty** for **gradient descent** method.

Cons:

- To reach the best result, we need to choose a resonable hyper parameter.

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