A PSF photometry tool for NASA's Kepler, $\mathcal{K}2$, and TESS missions

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Introduction

- NASA's Kepler and $\mathcal{K}2$ missions have been delivering high-precision time series data for a wide range of stellar types.
- However, both the official and community-developed pipelines [1–3] tend to focus on studying isolated stars using simple aperture photometry, which tends to perform sub-optimally in crowded fields and on faint stars. [4, 5].
- Although Point Spread Function (PSF) photometry methods are well known [4, 5], open source tools to perform PSF photometry specifically on Kepler and $\mathcal{K}2$ data are scarce. To address this issue, we present an open source PSF photometry toolkit for Kepler and $\mathcal{K}2$, and extensible to TESS, as part of the $\mathcal{K}2$ Guest Observer Office data analysis toolkit, PyKE, `https://www.github.com/KeplerGO/pyke`.
- The code for this poster is available at: `https://www.github.com/mirca/aas_poster`.

Methods

Fitting multiple PSFs jointly

Given an image with n pixels and m stars, we treat the pixel values Y_i as independent *non-identically* distributed Poisson random variables $\boldsymbol{Y} \triangleq \{Y_i\}_{i=1}^n$ such that $\mathbb{E}[Y_i] = \sum_{j=1}^m \lambda_i(\boldsymbol{\Theta}_j)$, where λ_i is the PSF model at the i-th pixel and $\boldsymbol{\Theta}_j$ is the vector of random variables which encode the flux and center of each star and the background.

The likelihood function of the pixel values given the model parameters can then be written as

$$P\left(\boldsymbol{Y}=\boldsymbol{y}\,\middle|\,\{\boldsymbol{\Theta}_j\}_{j=1}^m=\{\boldsymbol{\theta}_j\}_{j=1}^m\right)=\exp\left(-\sum_{i=1}^n\sum_{j=1}^m\lambda_i(\boldsymbol{\theta}_j)\right)\prod_{i=1}^n\frac{\left(\sum_{j=1}^m\lambda_i(\boldsymbol{\theta}_j)\right)^{y_i}}{y_i!}. \quad (1)$$

And the log likelihood function is

$$\log P\left(\boldsymbol{Y}=\boldsymbol{y}\,\middle|\,\{\boldsymbol{\Theta}_j\}_{j=1}^m=\{\boldsymbol{\theta}_j\}_{j=1}^m\right)=\sum_{i=1}^n\left(-\sum_{j=1}^m\lambda_i(\boldsymbol{\theta}_j)+y_i\log\sum_{j=1}^m\lambda_i(\boldsymbol{\theta}_j)\right). \quad (2)$$

Hence, the Maximum Likelihood Estimator can be formulated as the following optimization problem

$$\boldsymbol{\theta}^*(\boldsymbol{y}) = \arg\min_{\boldsymbol{\theta}\in\Lambda}\sum_{i=1}^n\left(\sum_{j=1}^m\lambda_i(\boldsymbol{\theta}_j)-y_i\log\sum_{j=1}^m\lambda_i(\boldsymbol{\theta}_j)\right). \quad (3)$$

Note that it is often necessary to impose prior probability densities on the model parameters to aid the optimization.

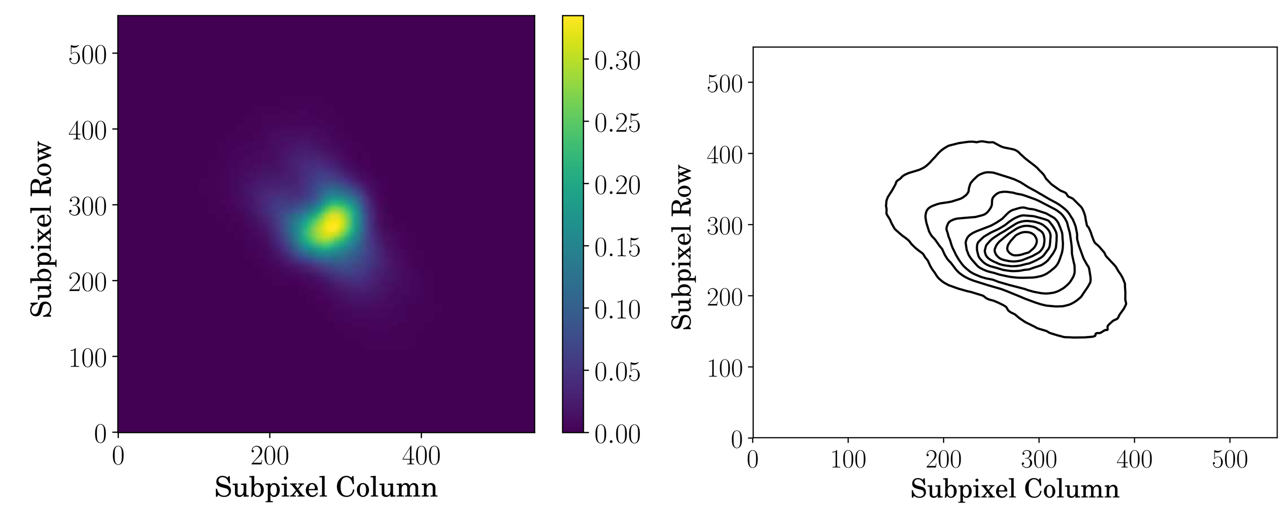
Estimating uncertainties using the Cramér-Rao Lower Bound

Uncertainties on the fitted parameters are approximated using the Cramér-Rao Lower Bound. Mathematically,

$$cov(\boldsymbol{\theta}^*(\boldsymbol{Y})) = \left(\mathbb{E}_{\boldsymbol{\theta}}\left[\nabla_{\boldsymbol{\theta}}\log p(\boldsymbol{Y}|\boldsymbol{\theta})\,[\nabla_{\boldsymbol{\theta}}\log p(\boldsymbol{Y}|\boldsymbol{\theta})]^T\right]\right)^{-1}\Big|_{\boldsymbol{\theta}=\boldsymbol{\theta}^*(\boldsymbol{y})} \quad (4)$$

The Kepler Pixel Response Function Model

- Kepler's pixel response function (PRF) has been shown to be nonsymmetric and spatially variant accross the detector [6].
- The PRF model used in PyKE is based on dithered data acquired during Kepler's comissioning phase [6].

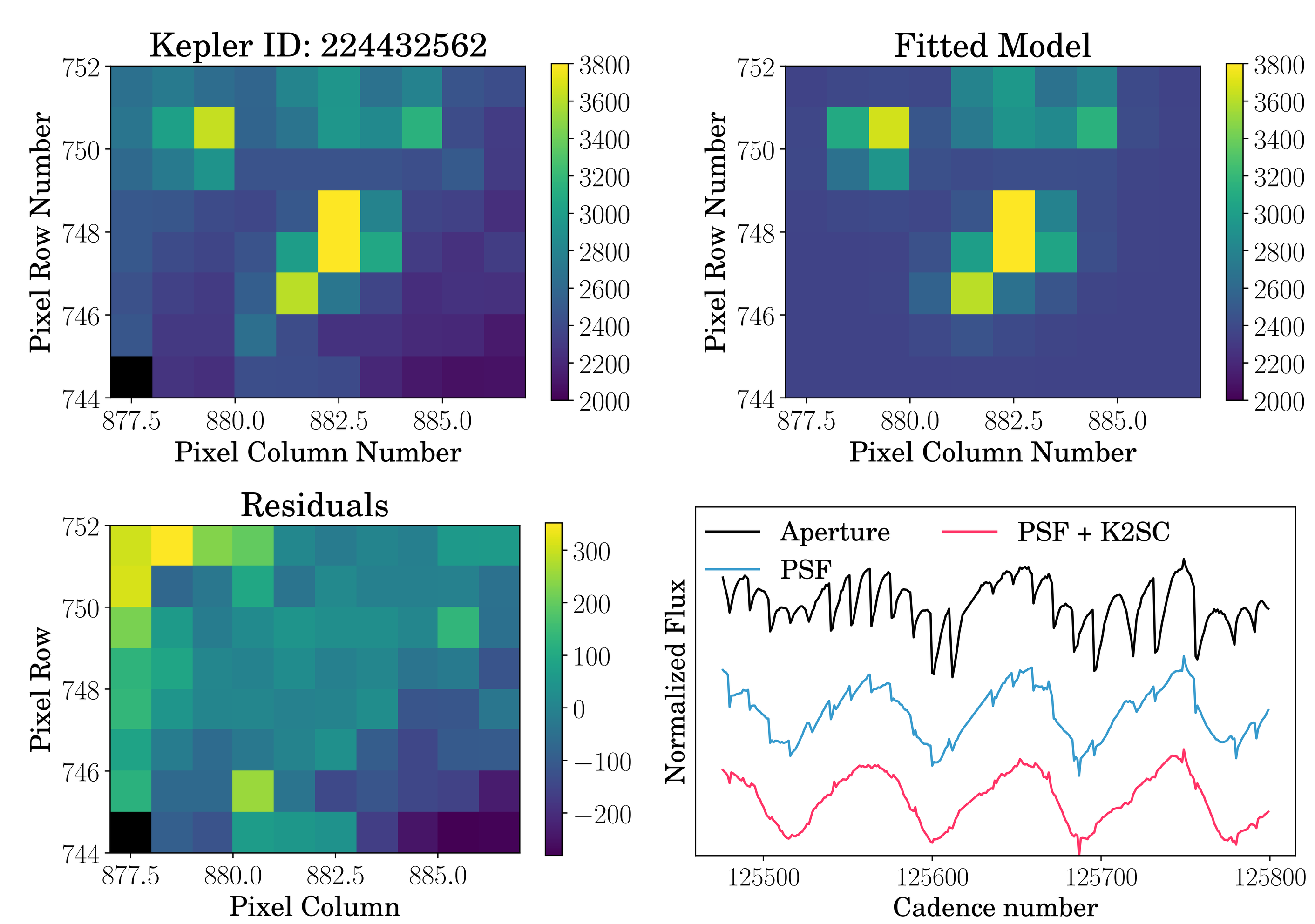


Using the PyKE package in Python, the PSF model for a given detector position can be instantiated using the information contained in Kepler Target Pixel File (TPF) header:

```
>>> from pyke import KeplerTargetPixelFile
>>> tpf = KeplerTargetPixelFile("PATH")
>>> prf = tpf.get_prf_model()
```

Crowded K2 Clusters

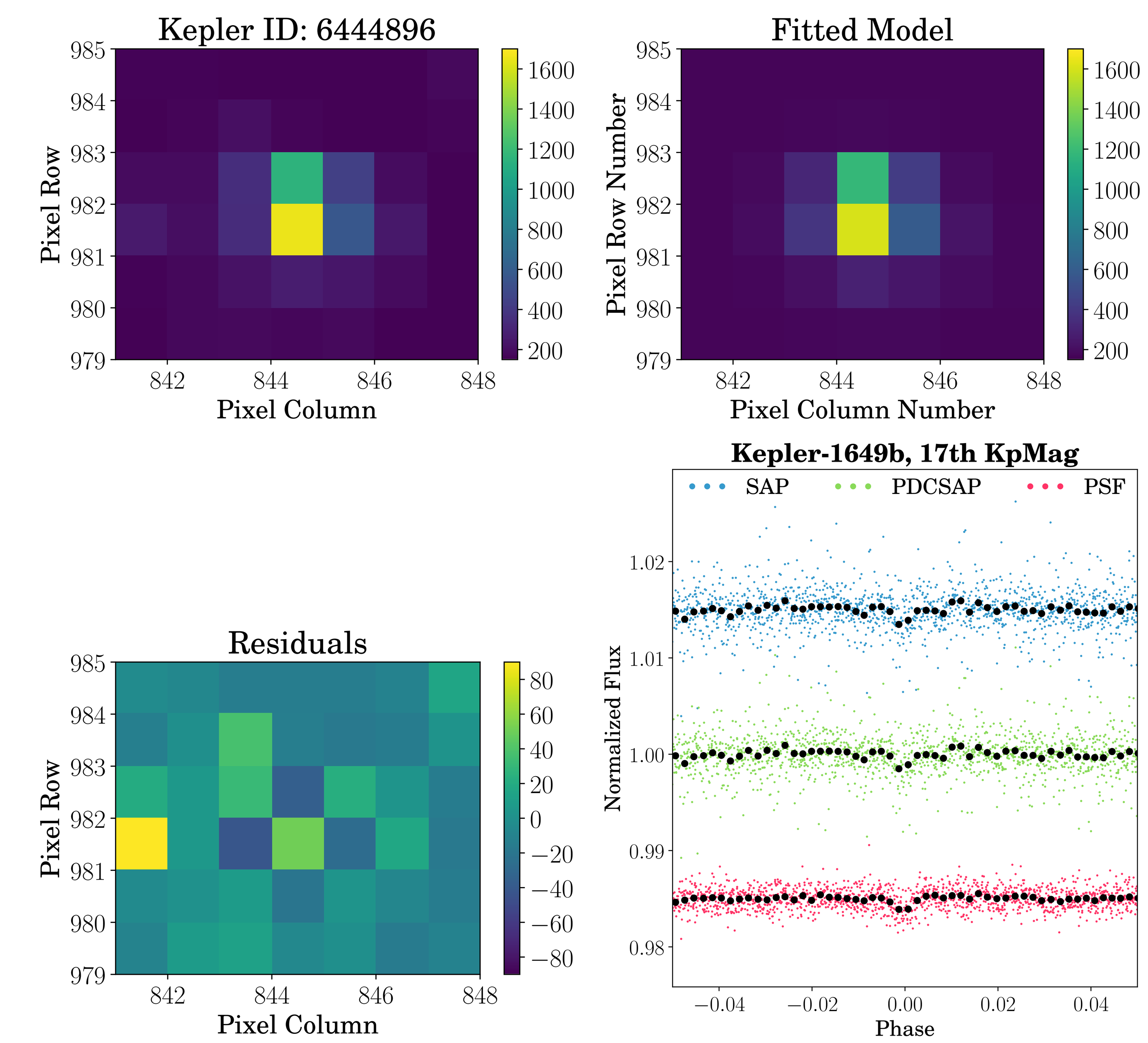
Having instantiated suitable PSF models for a set of stars, we can use PyKE to fit the joint model to the data. In the example shown here, we simultaneously fit five stars in data from the crowded Lagoon Nebula cluster observed during $\mathcal{K}2$ Campaign 9. For the 14th-magnitude star shown in the center of the cutout below, we find that PSF photometry yields a lightcurve that is ≈ 3 times more precise compared to aperture photometry.




```
>>> from pyke.prf import SceneModel, PRFPhotometry
>>> scene = SceneModel(prfs=5*[prf])
>>> phot = PRFPhotometry(prior=prior, scene_model=scene)
>>> results = phot.fit(tpf.flux)
```

Kepler Faint Stars

In addition to being necessary in crowded fields, we find that PSF photometry also benefits the light curves of isolated faint stars. For example, star `KIC 6444896` is known to contain a small planet, Kepler-1649b [7]. Using PSF photometry, we recover the planet signal which is ≈ 1.67 times more precise compared to the aperture photometry employed by the official Kepler pipeline. Although the latter could be improved by tweaking the aperture mask of the source, the fact that PSF photometry is not sensitive to the choice of an aperture mask is a significant practical benefit.



Conclusions

- We have presented an open-source tool to perform PSF photometry on Kepler and $\mathcal{K}2$ data.
- For crowded clusters and faint stars, we find that PSF photometry can outperform aperture photometry.
- In future work, we intend to infer the PSF model from nearby stars to improve the accuracy of the fit. We will also study the performance as a function of stellar brightness and crowding.

References

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