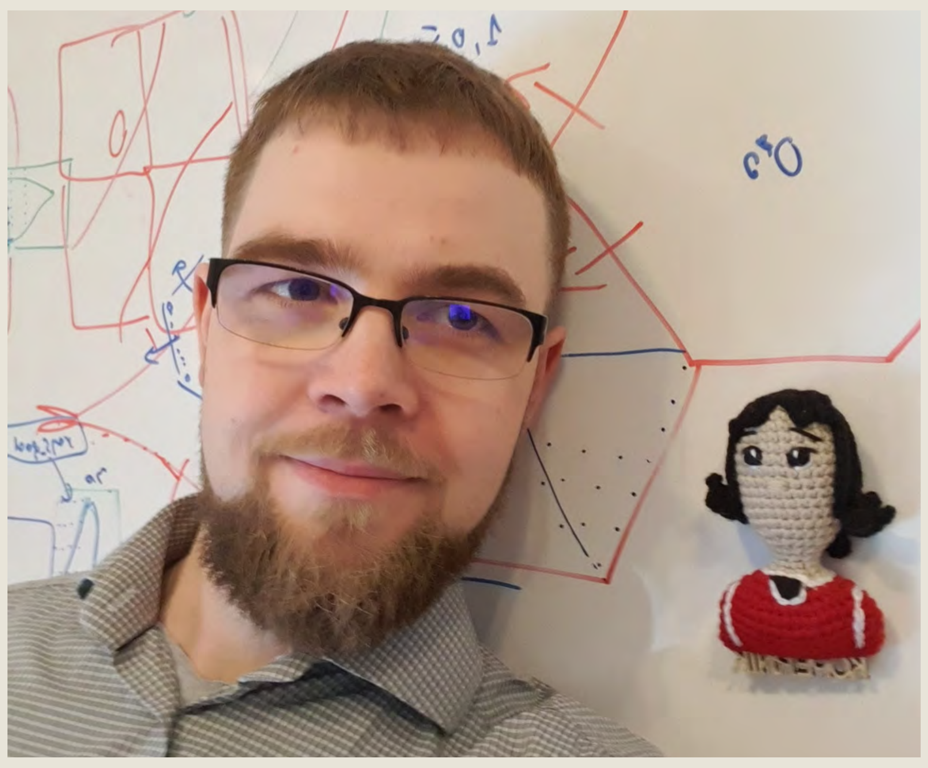


rpoleski@astrouw.edu.pl

How to derive planet occurrence rate using microlensing events with degenerate solutions?

Astronomical Observatory of the University of Warsaw

Founded in 1825

Radek Poleski, Maciej Burzyński, Gabriela Karasim-Piotrowska, Paweł Maliński, Jakub Suchecki, Marcin Gmyrek

Introduction

One of main goals of many current microlensing research is to derive the occurrence rate of exoplanets. To do that we need to: detect planets, measure their parameters, calculate detection efficiency, and combine these pieces of information. **How we should treat planets with degenerate solutions?** Most frequent degeneracy is for separation of *s* and of 1/*s*. In some cases there is no way to distinguish these separations based on photometric data.

Previous research: Suzuki et al. 2016

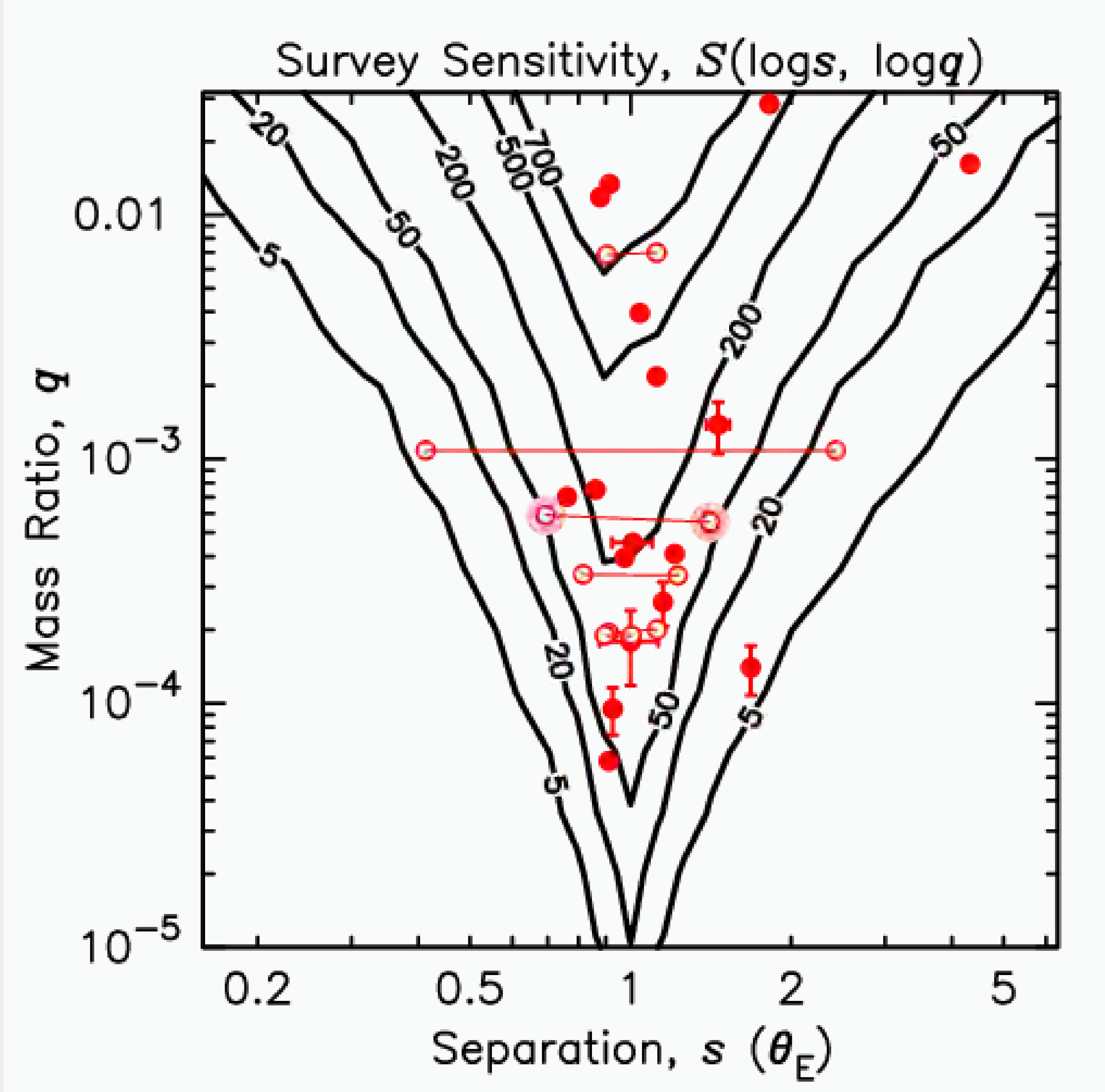
This plot from Suzuki et al. (2016) shows:

- survey sensitivity (equivalent to detecion efficiency): number of planets that MOA survey would be if every star had a planet at a given separation *s* and mass ratio *q* - shown by **black countour lines with numbers**,
- detected planets - **red points**; for degenerate models there are **red lines** connecting these models.

Then they used Bayesian analysis and fitted occurrence rate parametrized as:

$$\frac{d^2N_{\rm pl}}{d\log q\; d\log s} = A\left(\frac{q}{q_{\rm br}}\right)^n s^m \quad \text{for } q > q_{\rm br}$$
$$= A\left(\frac{q}{q_{\rm br}}\right)^p s^m \quad \text{for } q < q_{\rm br},$$

where q_br was fixed at 1.7E-4.
For planets with degenerate models, they weighted solutions according to exp(-0.5 Delta chi^2). We expect this approach **to bias the parameter *m*** to a lower value.



Hierarchical Bayesian modeling

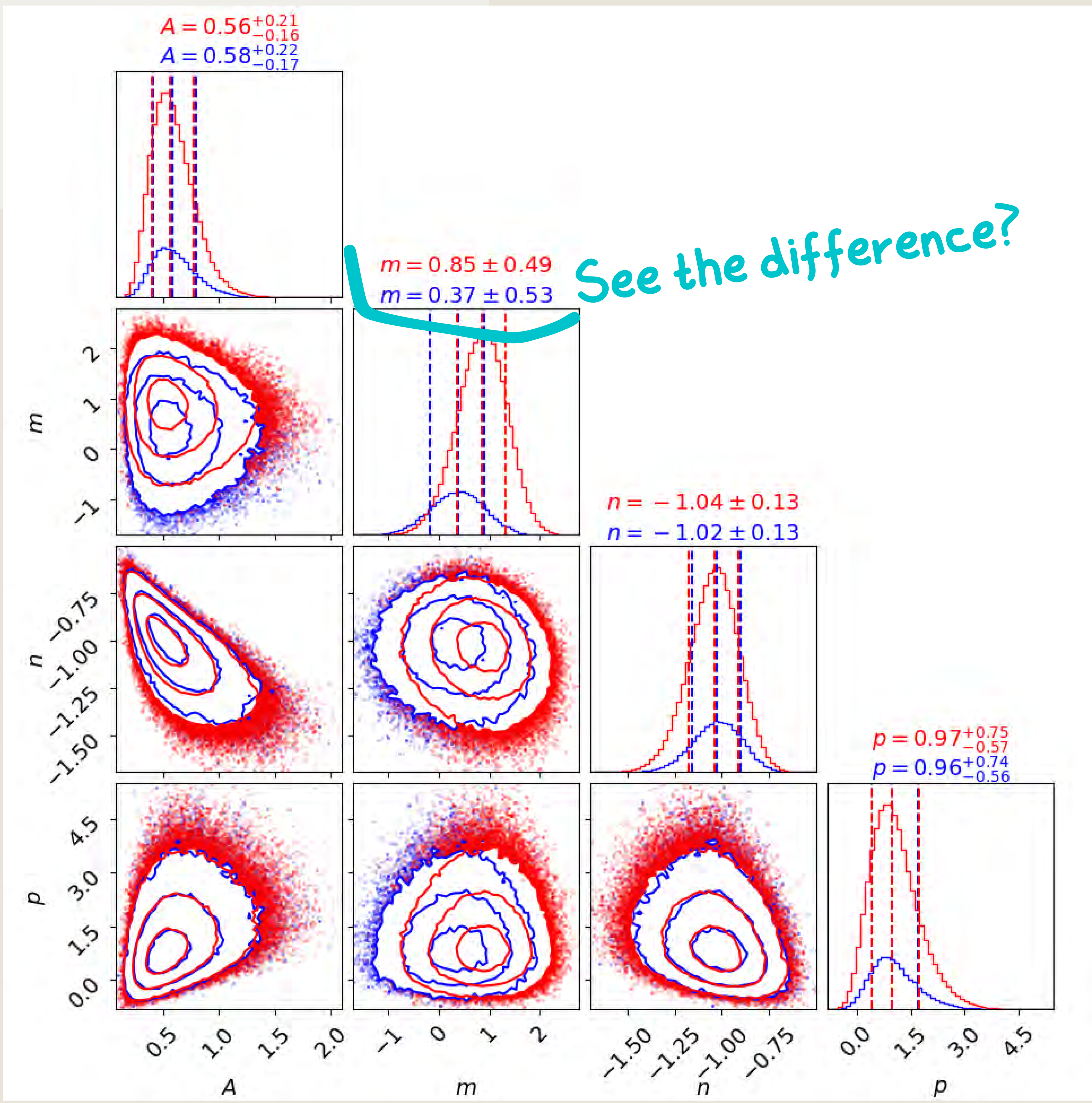
Hierarchical Bayesian modeling combines information on different levels (or hierarchies). In the present case, there is planets' population level and individual planet level. The likelihood depends on parameters of both levels and while running MCMC or MultiNest all these parameters are changed.

Hierarchical models are frequently used to derive population parameters from a population of objects with significant uncertainties in their properties, e.g.:

- radii of planets from the Kepler transit survey (Foreman-Mackey et al. 2014).
- parallaxes (including negative ones) in order to derive distances (Luri et al. 2018, Bailer-Jones et al. 2021).

Our approach and results

We use the data from Suzuki et al. (2016) - thanks for releasing the survey sensitivity!
The planet occurrence model has 4 parameters (*A, m, n, p*) and we add 4 more: a flag for each planet with degenerate models that indicates if *s<1* or *s>1* model should be used in the likelihood evaluation of given set of parameters. Then we run MCMC for all 8 parameters.
Results: out of 4 degenerate planets only **1 affects results**. The **corner plot on the right** shows four main parameters for ***s*=0.41 in blue** and ***s*=2.43 in red**. The exponent *m* changes by 1 sigma. Other parameters are unchanged.
We also obtain posterior probability for *s*=2.43 solution of 0.80. This is based on assumption that the planet is drawn from the same population as the rest.
Suzuki et al. (2016) found ***m* = 0.62+-0.57**. We're finding 0.77+-0.54 using the same data. Poleski et al. (2021) found 1.09+-0.64 based on the OGLE planets with 2 < *s* < 6.



Discussion

It turned out that depending on which solution we choose for one of the planets affects the parameter *m* on a 1 sigma level. **There were 22 planets studied and the result is affected by only a single planet.** Hence, we should carefully investigate degenerate models while deriving planet occurrence rate.
This approach can be extended to take into account other effects, e.g., events with unclear interpretation.

Acknowledgements. Work by RP was supported by Polish National Agency for Academic Exchange grant "Polish Returns 2019."

References

1. Bailer-Jones et al. 2021, AJ, 161, 147
2. Foreman-Mackey, Hogg, and Morton 2014, ApJ 795, 64
3. Luri et al. 2018, A&A 616, 9
4. Poleski et al. 2021, AcA 71, 1
5. Suzuki et al. 2016, ApJ 833, 145