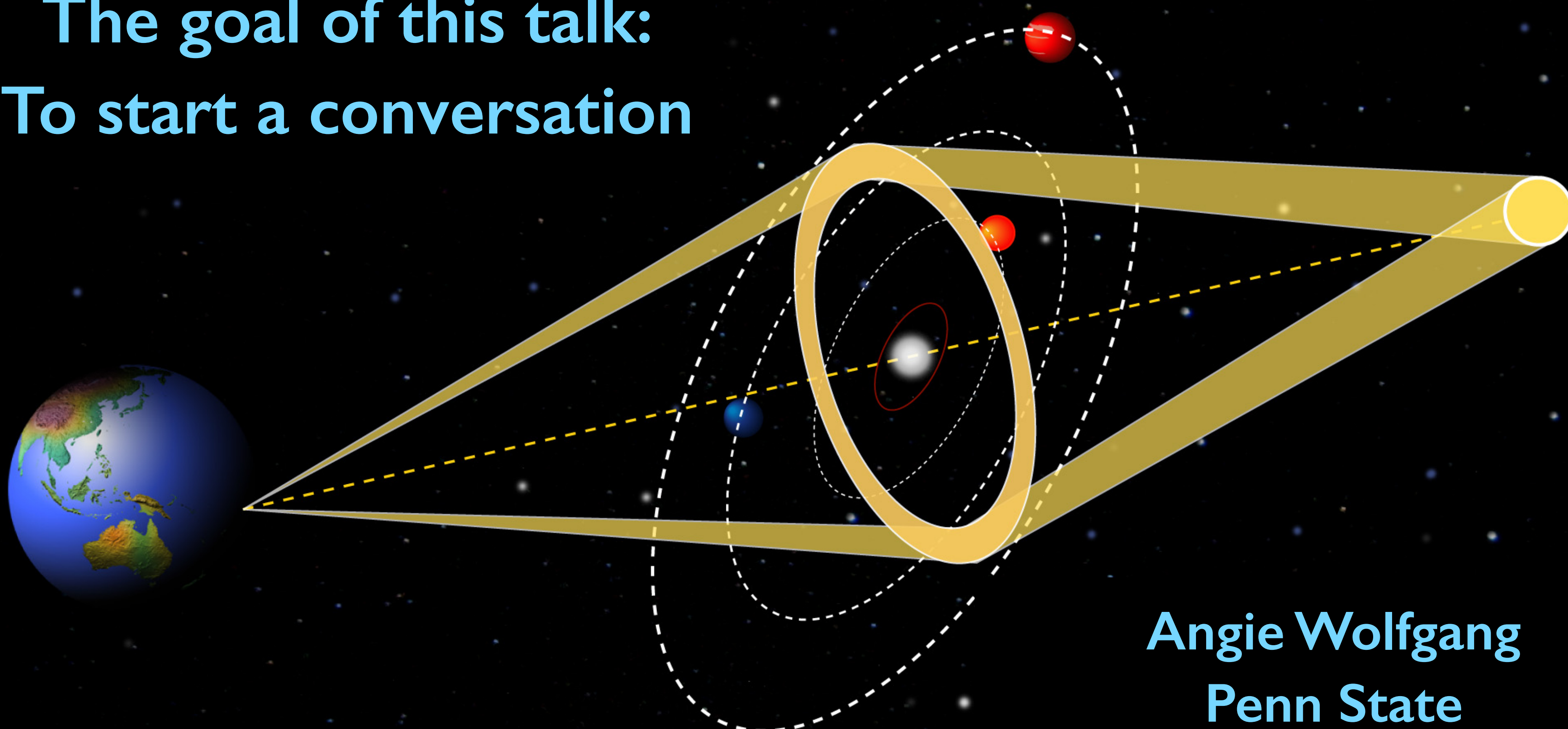
Statistical Opportunities in Microlensing

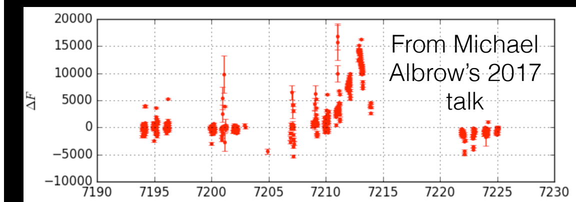
The goal of this talk:
To start a conversation

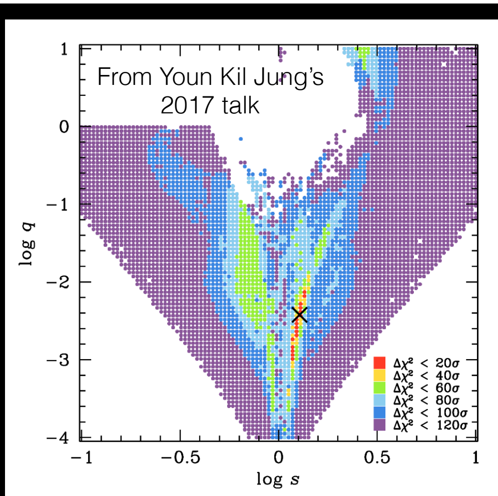


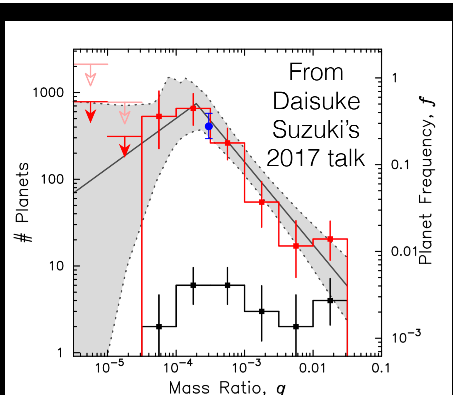
Angie Wolfgang
Penn State
NSF Postdoctoral Fellow

Problems and Opportunities:

“Closer” to light curves (i.e. more data-centric)







- Correlated noise in light curves - how does a more advanced noise model change your inferred parameter values?
- Computationally expensive ray-shooting codes - can statistical emulation speed up microlensing parameter estimation?
- Likelihood of data given parameters can be multimodal, and caustic topographies are not continuous - how to choose the best model?
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“Farther” from light curves (i.e. more model-centric)

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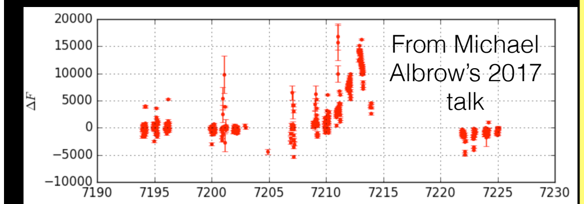

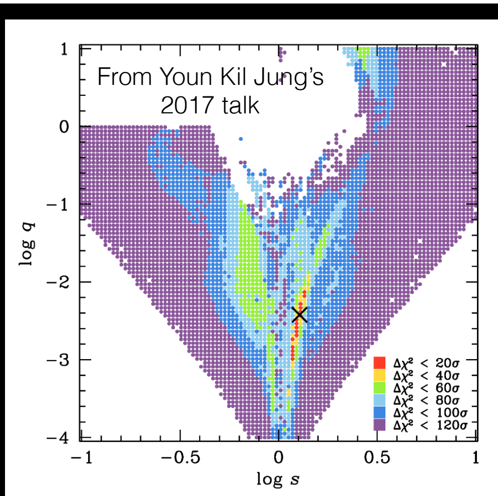

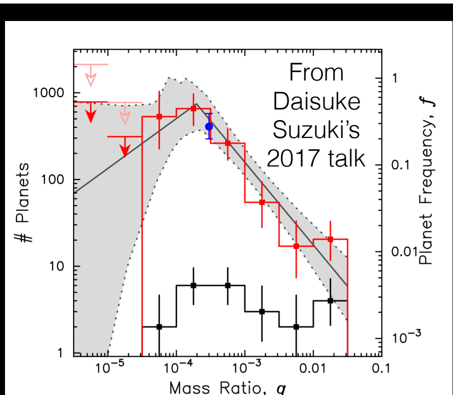

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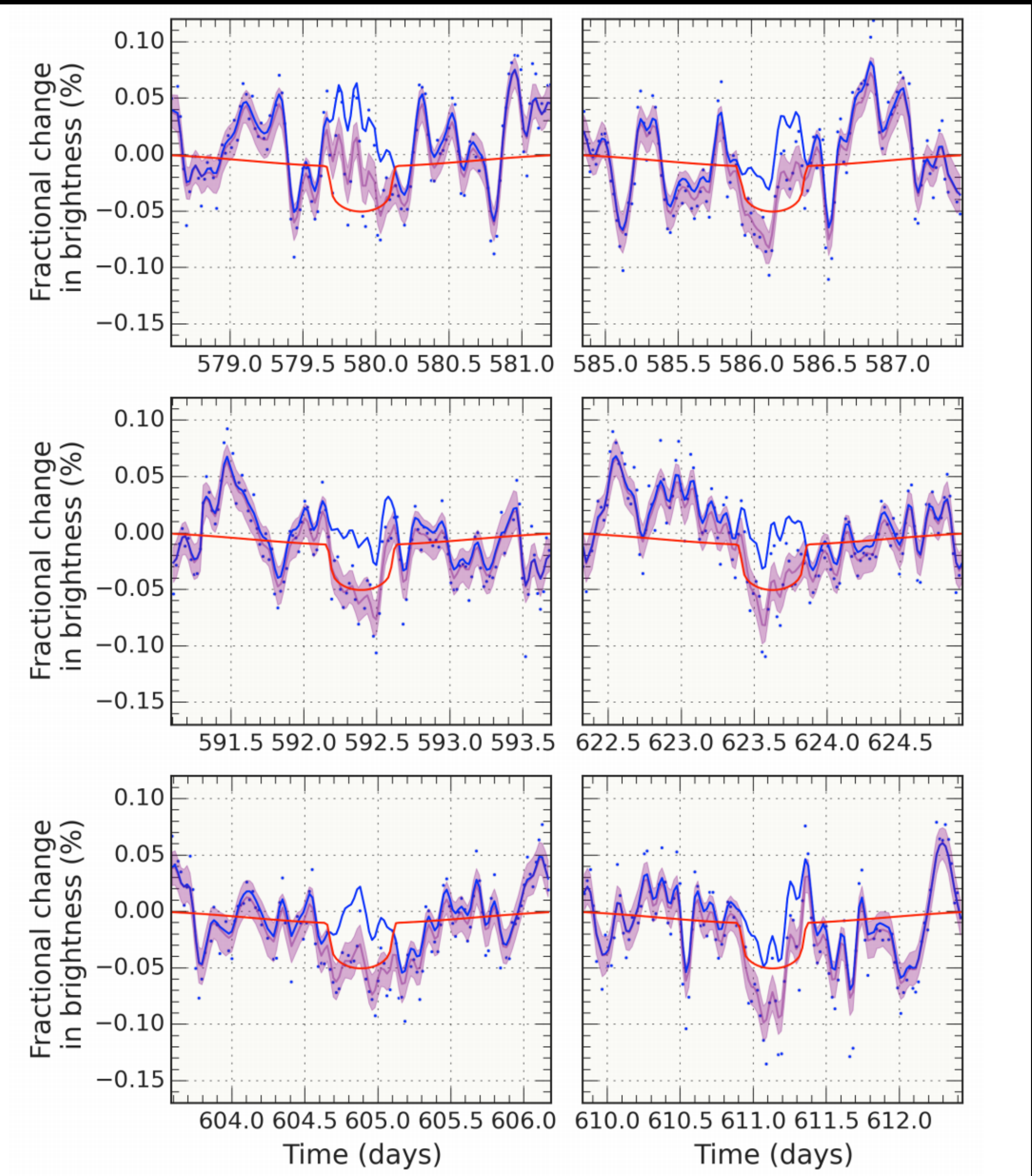
Correlated Noise

Lesson learned from transits: Kepler-91 b (Barclay et al. 2015)



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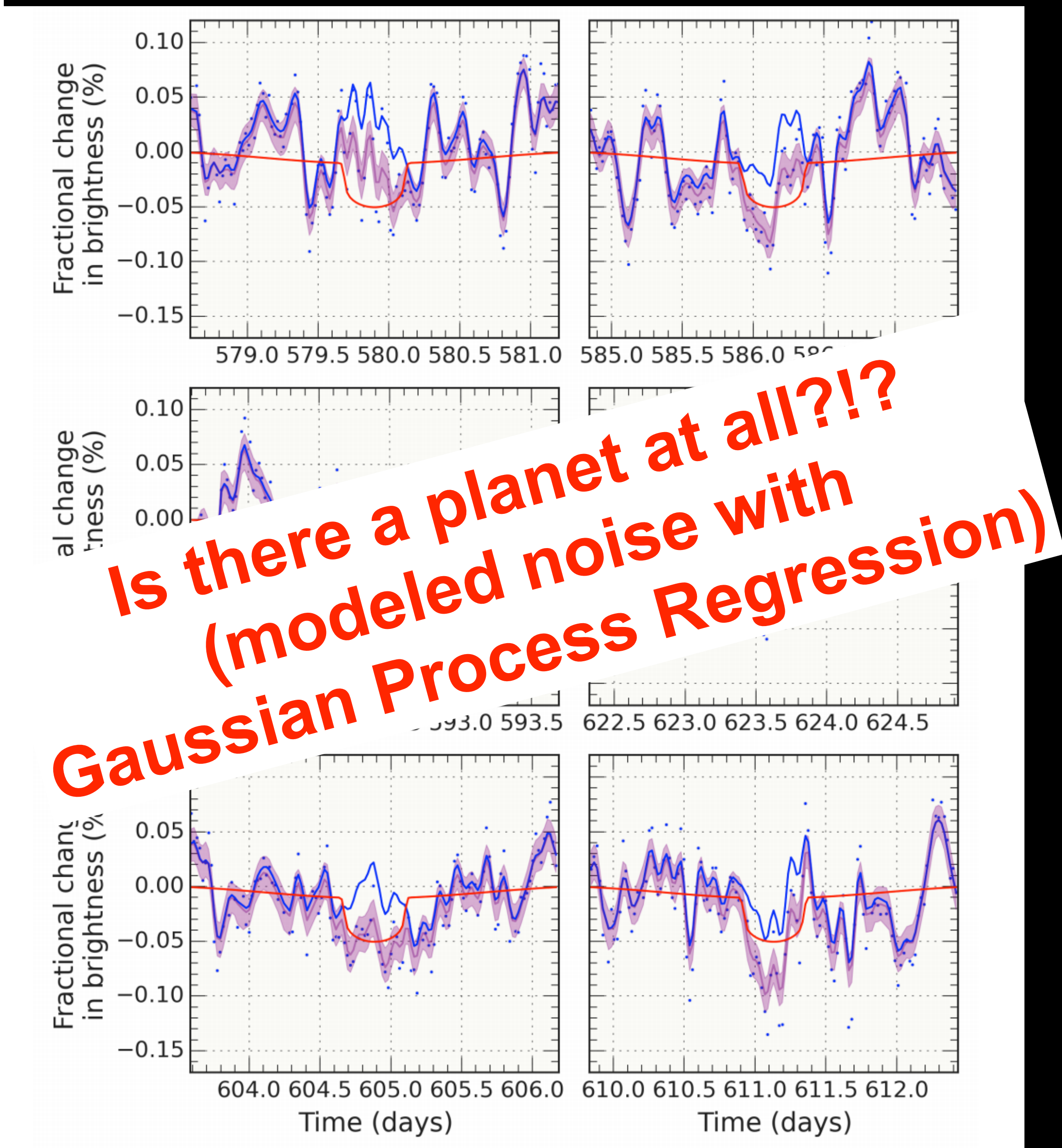

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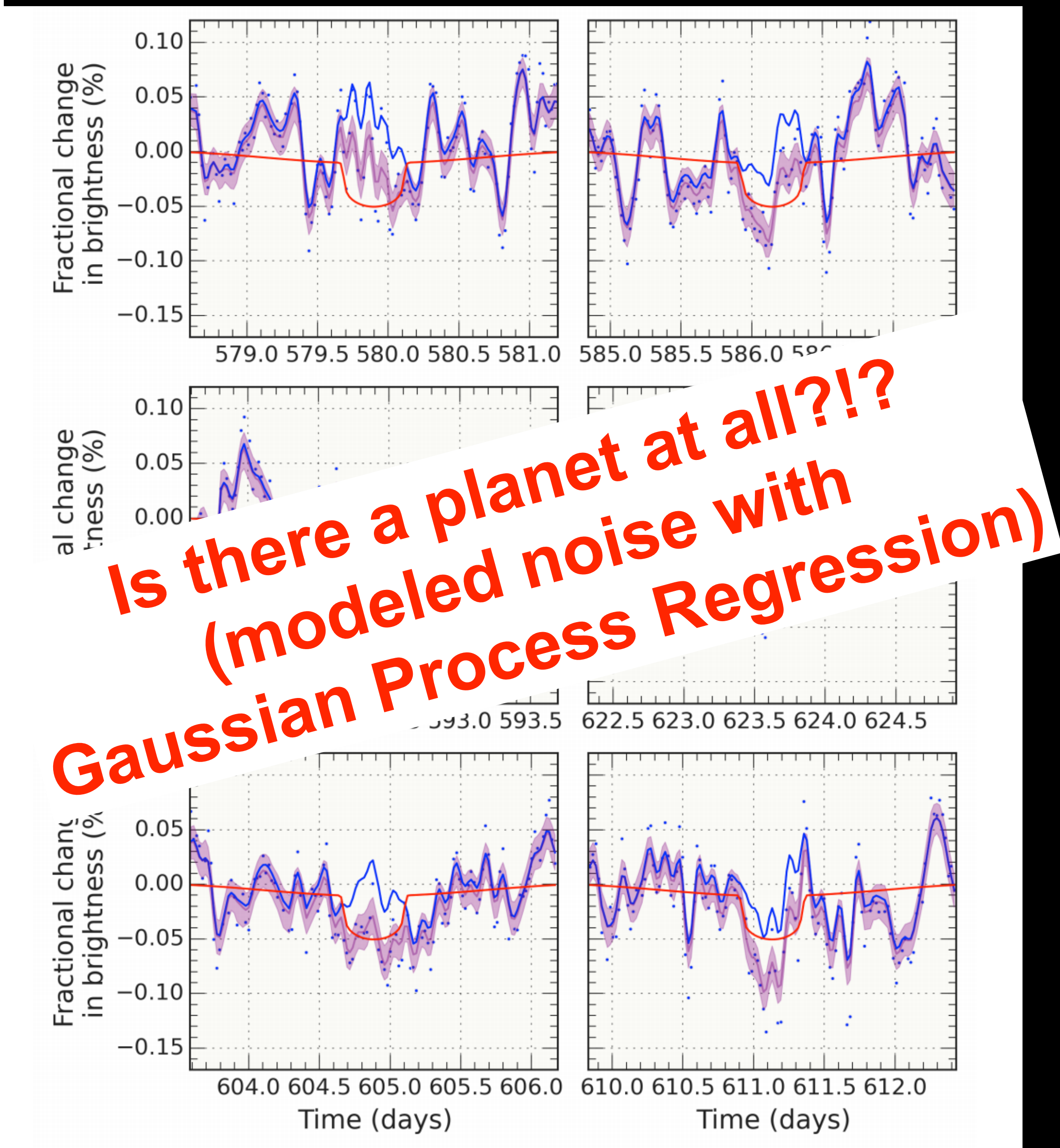

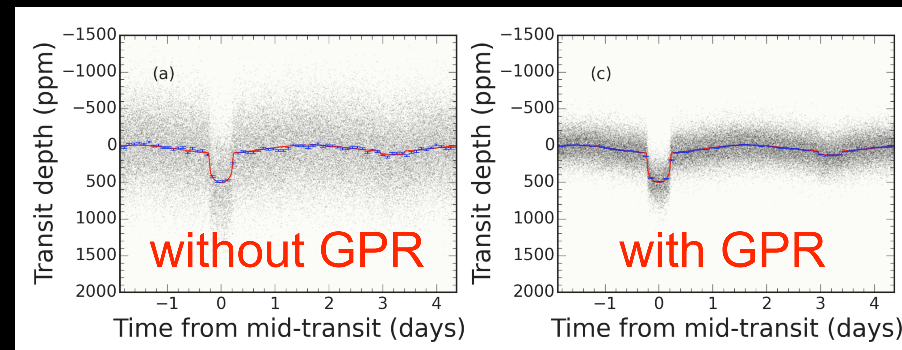

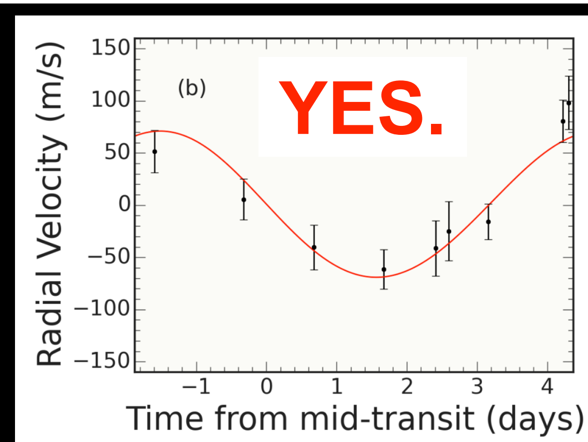

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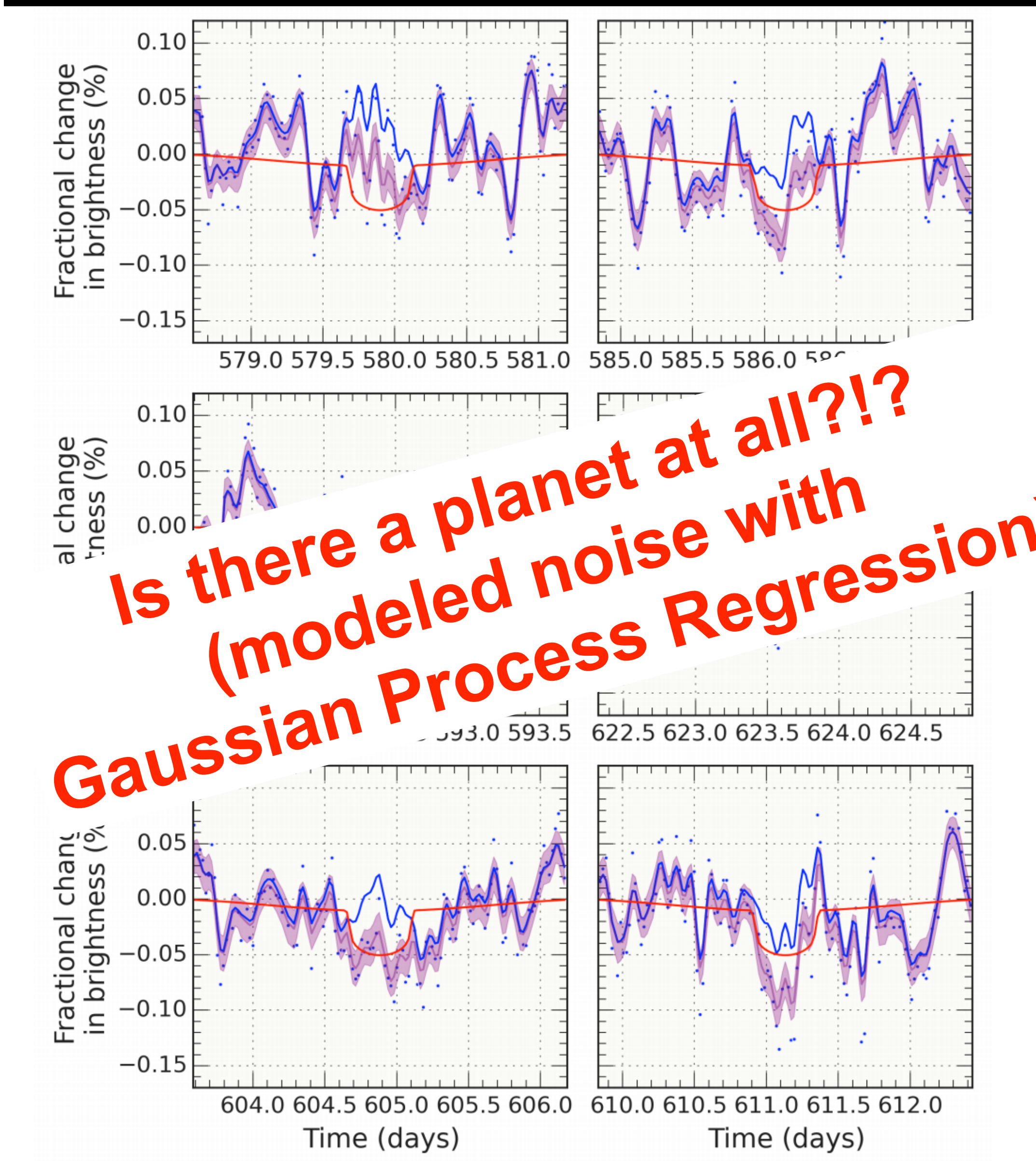
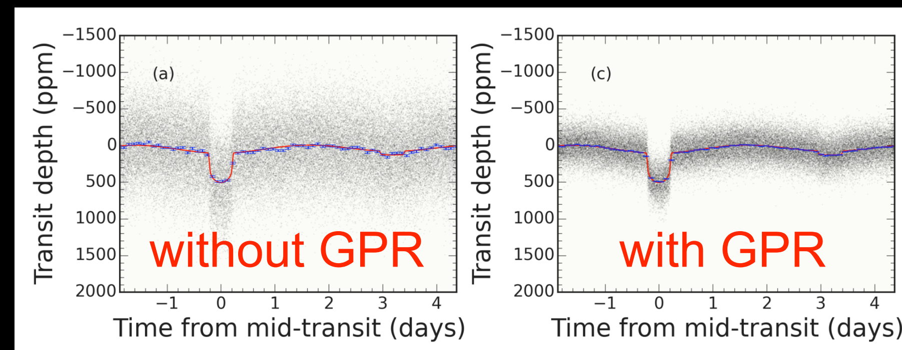
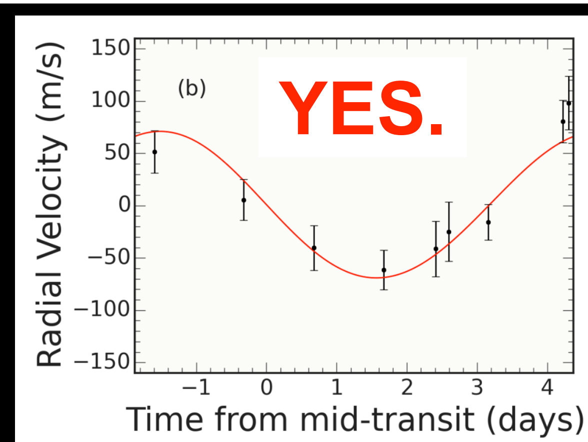


Is there a planet at all?!?
(modeled noise with Gaussian Process Regression)



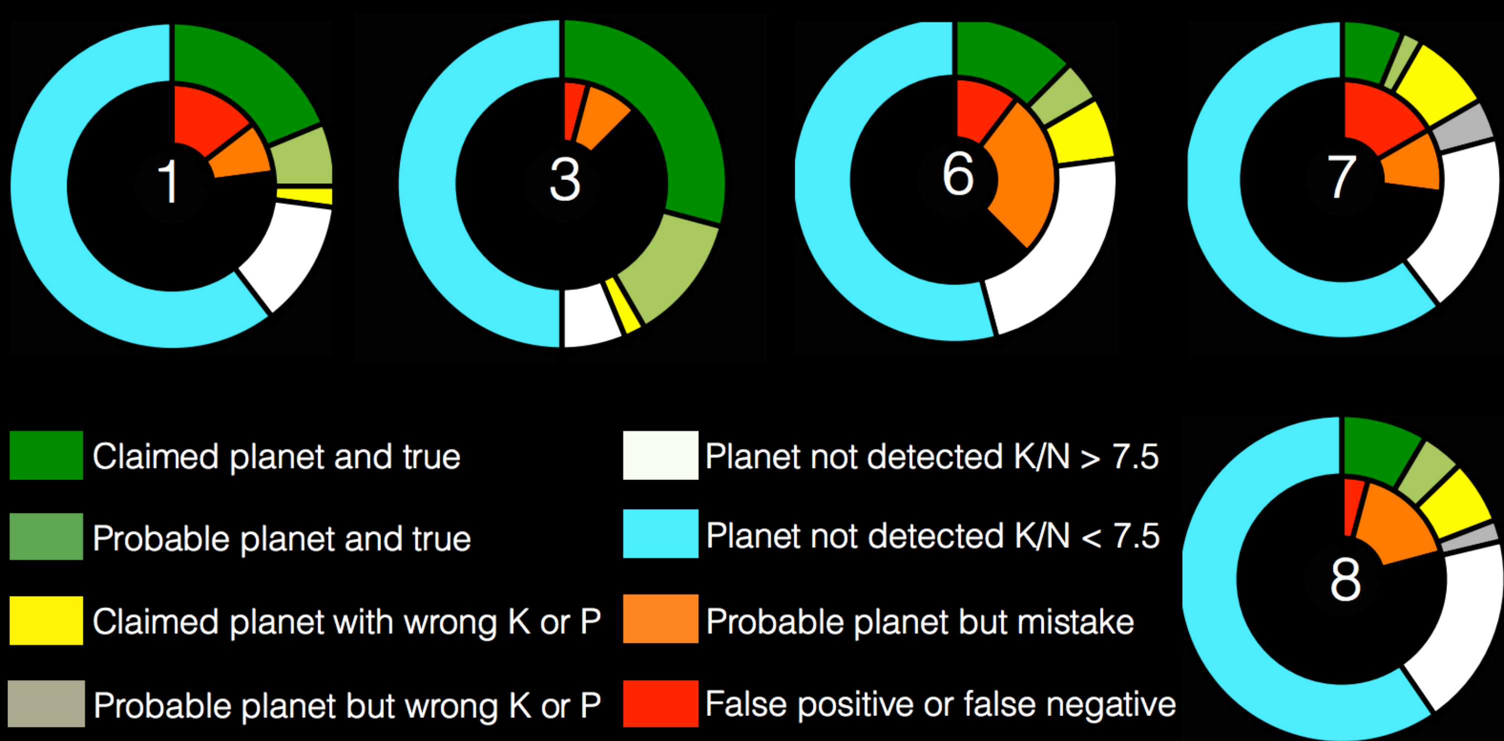


1) Correlated noise can be significant for red giants (common μlensing source)
2) Can drastically change your detections & parameter values!

Correlated Noise

Lesson learned from radial velocities: RV Fitting Challenge

	Team	Techniques
1	Torino	Bayesian framework with Gaussian process to account for red noise
2	Oxford	Bayesian framework with Gaussian process to account for red noise
3	M. Tuomi	Bayesian framework with Moving Average to account for red noise
4	P. Gregory	Bayesian framework with apodized Keplerians to account for red noise
5	Geneva	Bayesian framework with white noise
6	A. Hatzes	Pre-whitening
7	Brera	Filtering in frequency space
8	IMCCE	Compressed sensing and filtering in frequency space (preliminary results)

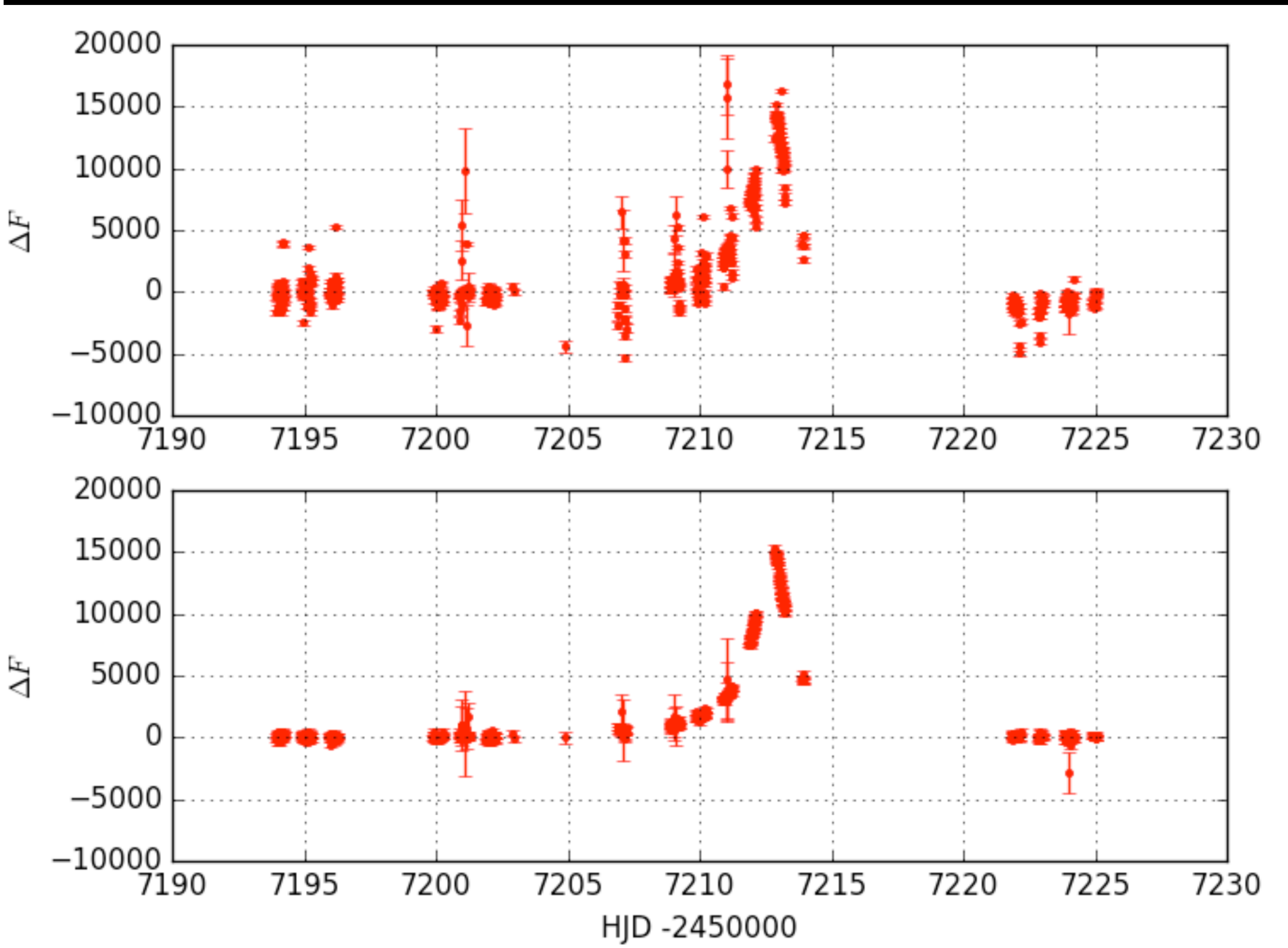


(Dumusque et al. 2017)

1) A Bayesian framework + red noise model produces more reliable and complete detections.
2) Inflexible noise models more often lead to inaccurate parameter values.

Correlated Noise

Effect on microlensing parameters (from Albrow's 2017 talk)



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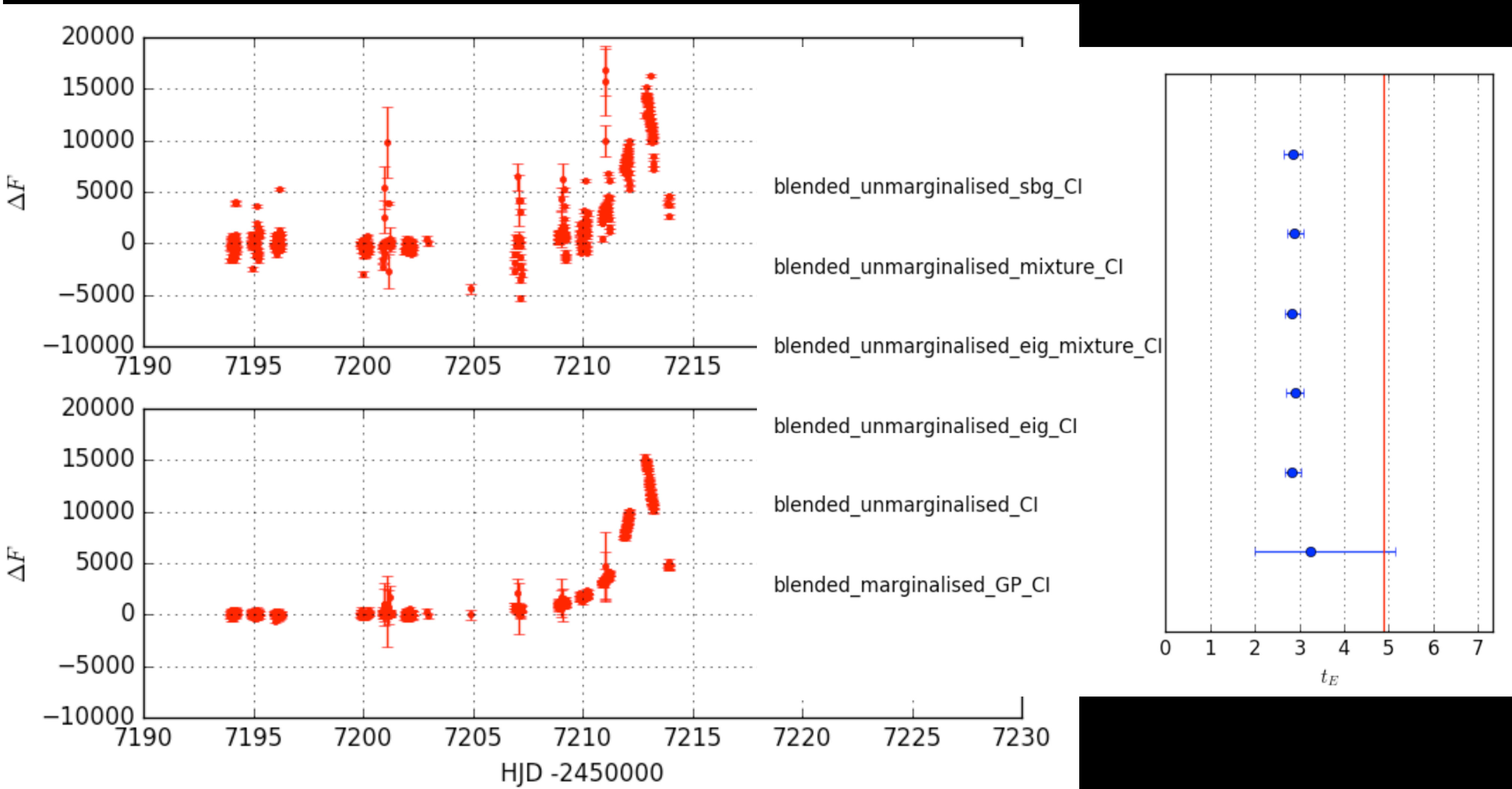
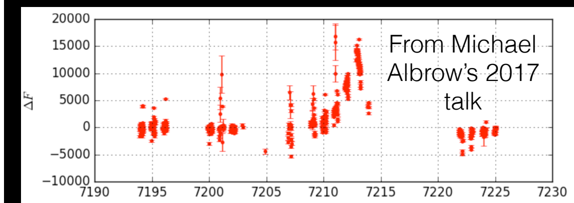


Red noise can seriously mislead you, too!! Test more than t_E!

Problems and Opportunities:

"Closer" to light curves (i.e. more data-centric)



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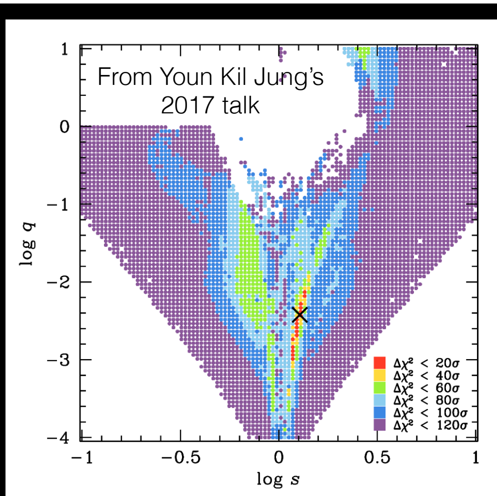
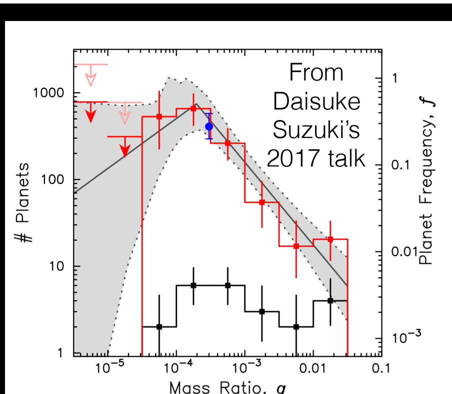


- Computationally expensive ray-shooting codes - can statistical emulation speed up microlensing parameter estimation?



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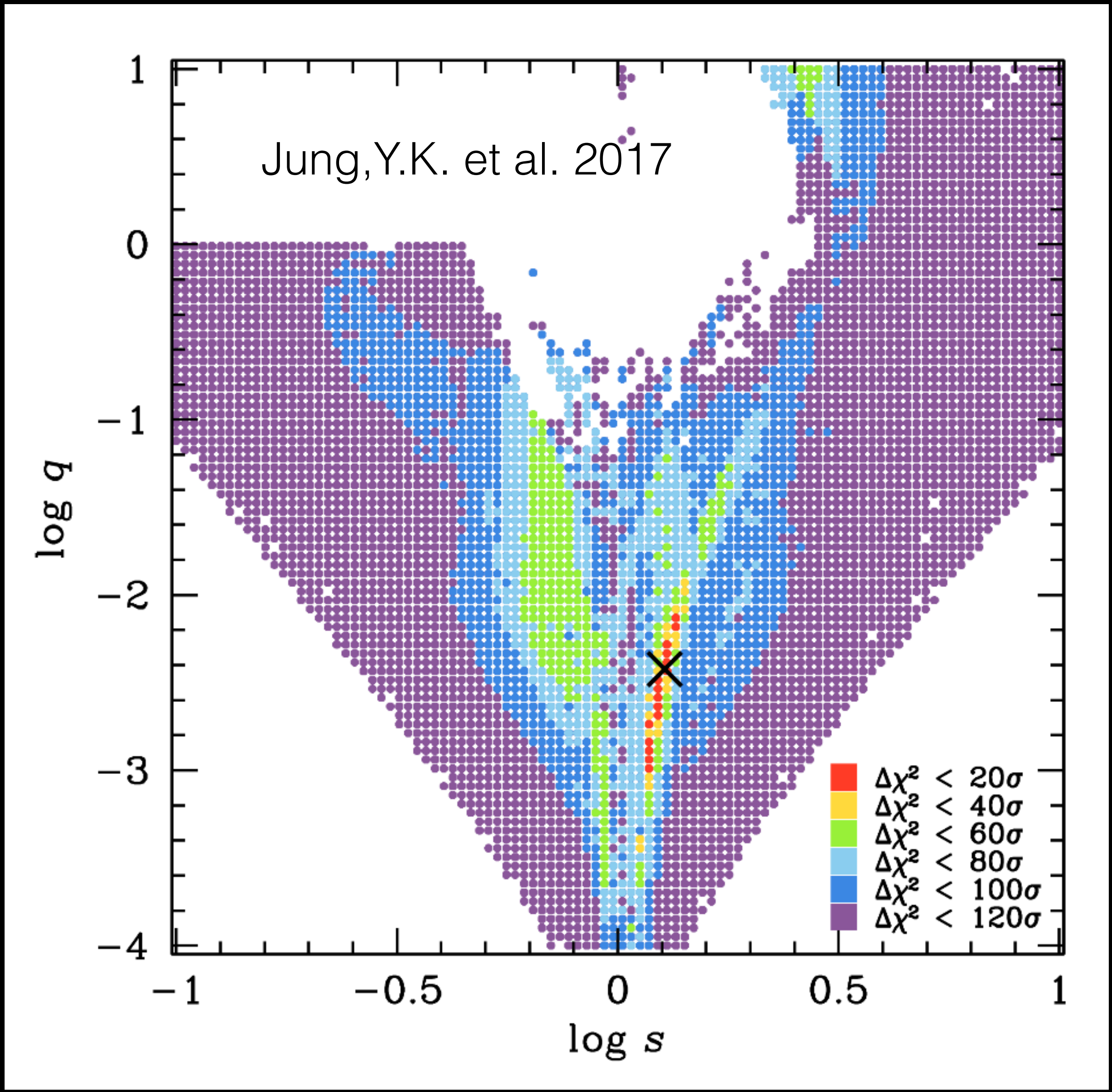
"Farther" from light curves (i.e. more model-centric)

Statistical Emulation

of computationally expensive astrophysical simulations

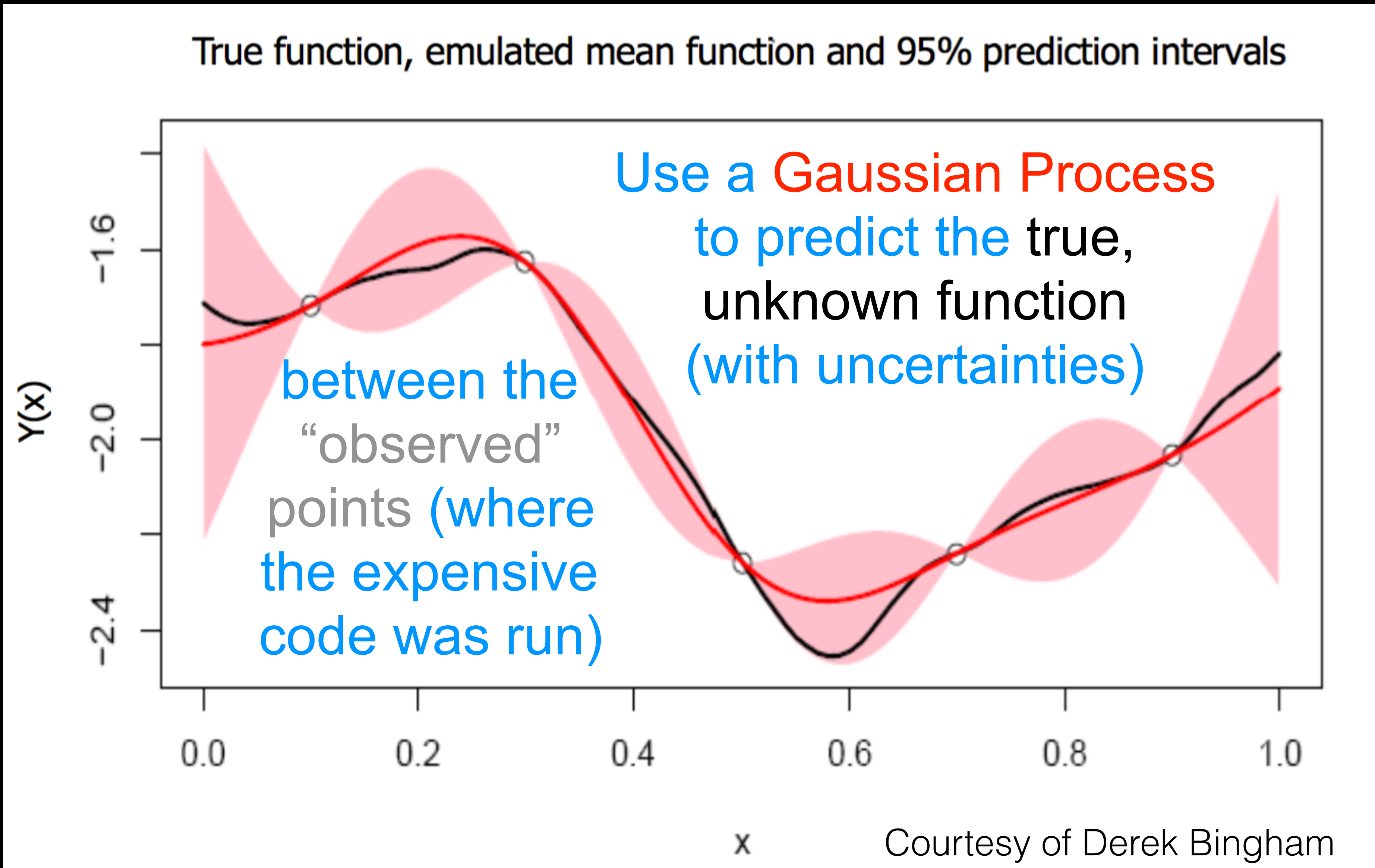


Is there a more efficient way to compute the grids of q, s, and α?

YES: statistical emulation
. . . plus it allows you to interpolate the grid for free
. . . plus that interpolation is probabilistic

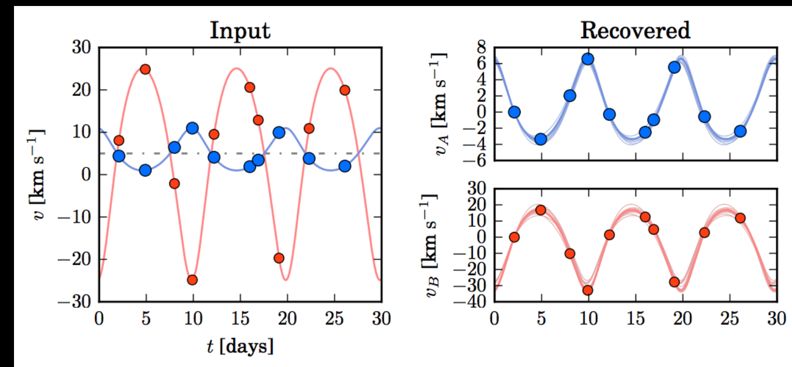
Statistical Emulation

A 1-dimensional conceptual example

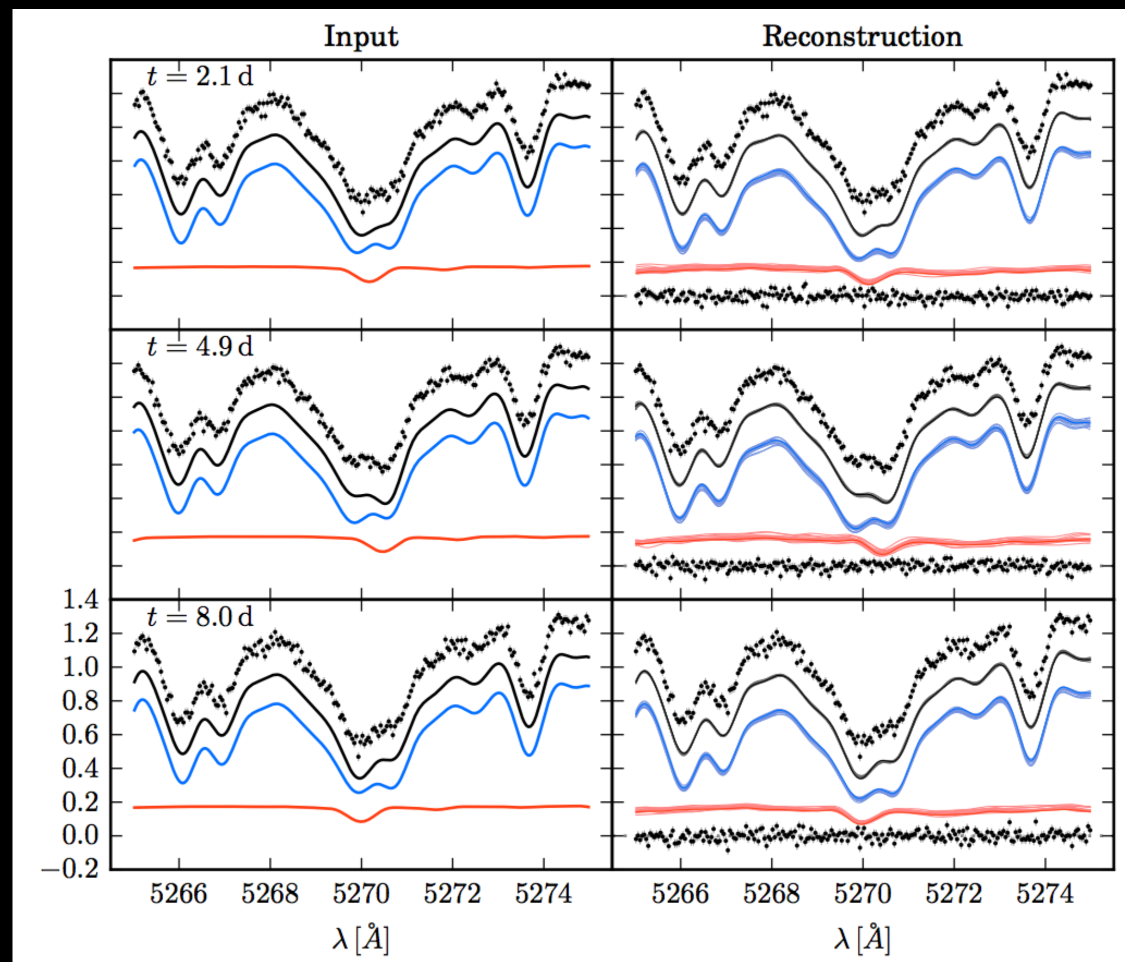


Statistical Emulation

A multi-dimensional astrophysical example (Czekala et al. 2017)



Simulated the time-varying spectrum of an SB1 binary star system



Used a Gaussian Process emulator to model the spectrum, predict/interpolate the radial velocities of each component, and infer both stars' masses.

Problems and Opportunities:

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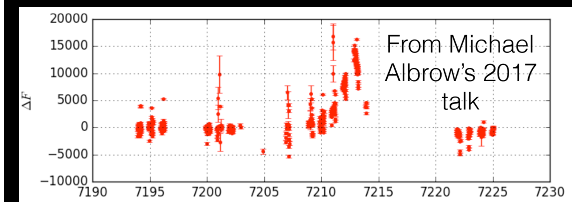

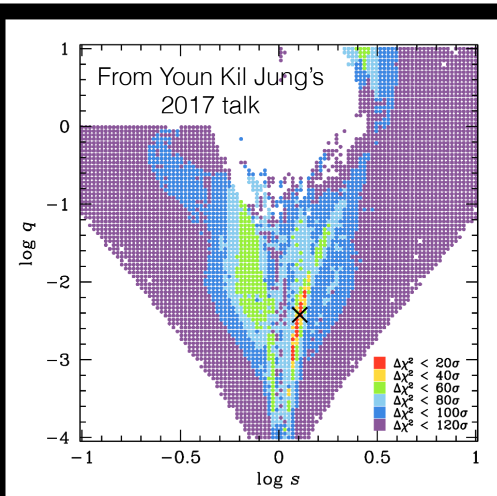

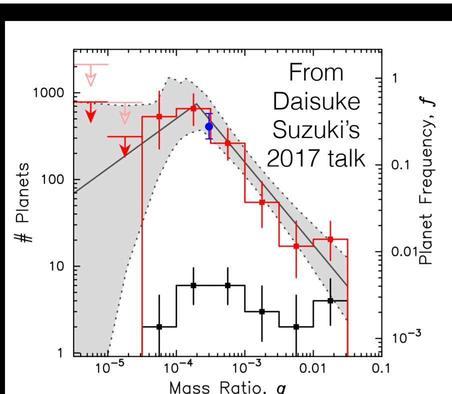

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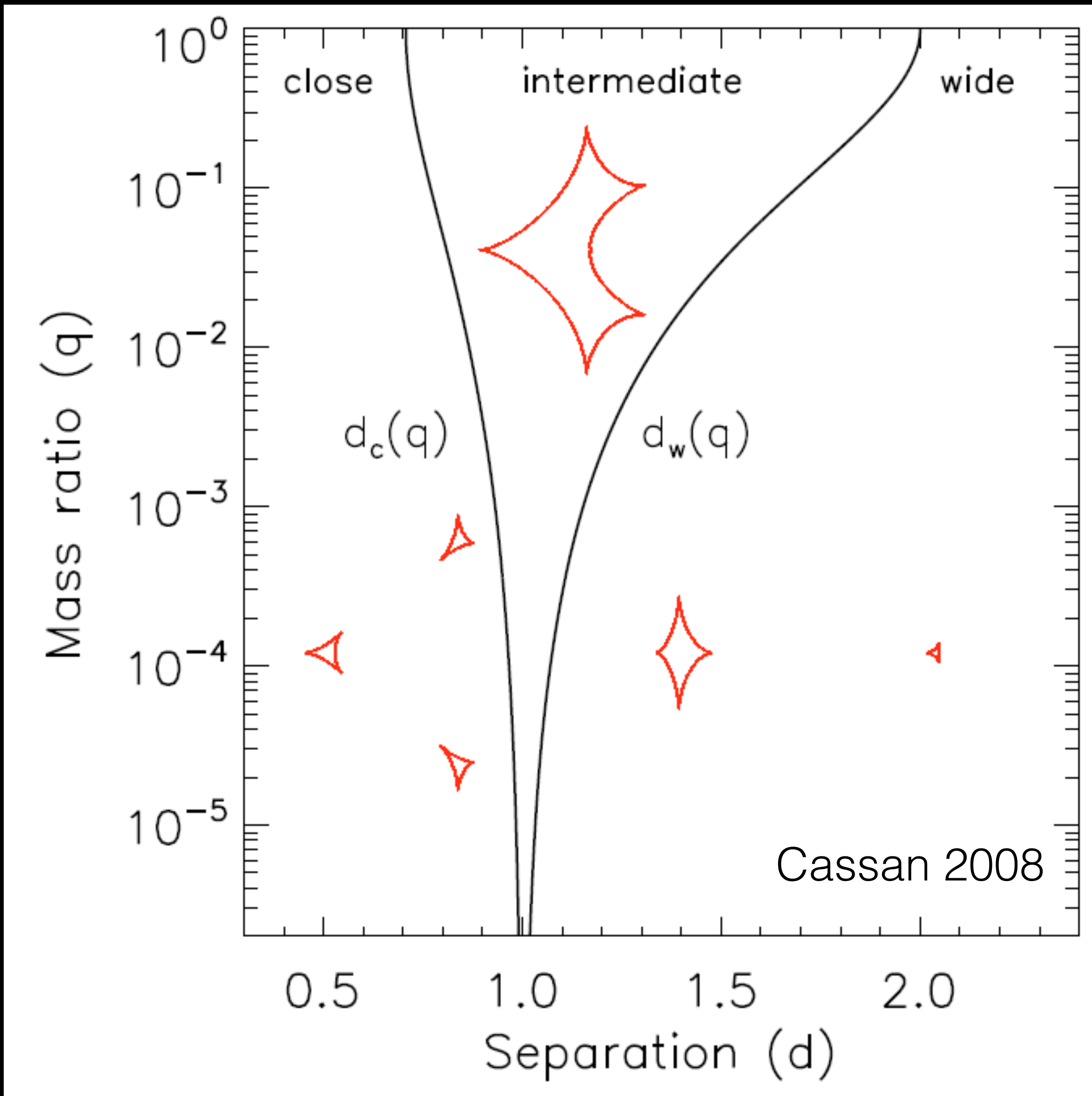
Model Comparison

Which caustic topology best fits the data?



Actually have 3 separate models to fit to the data …

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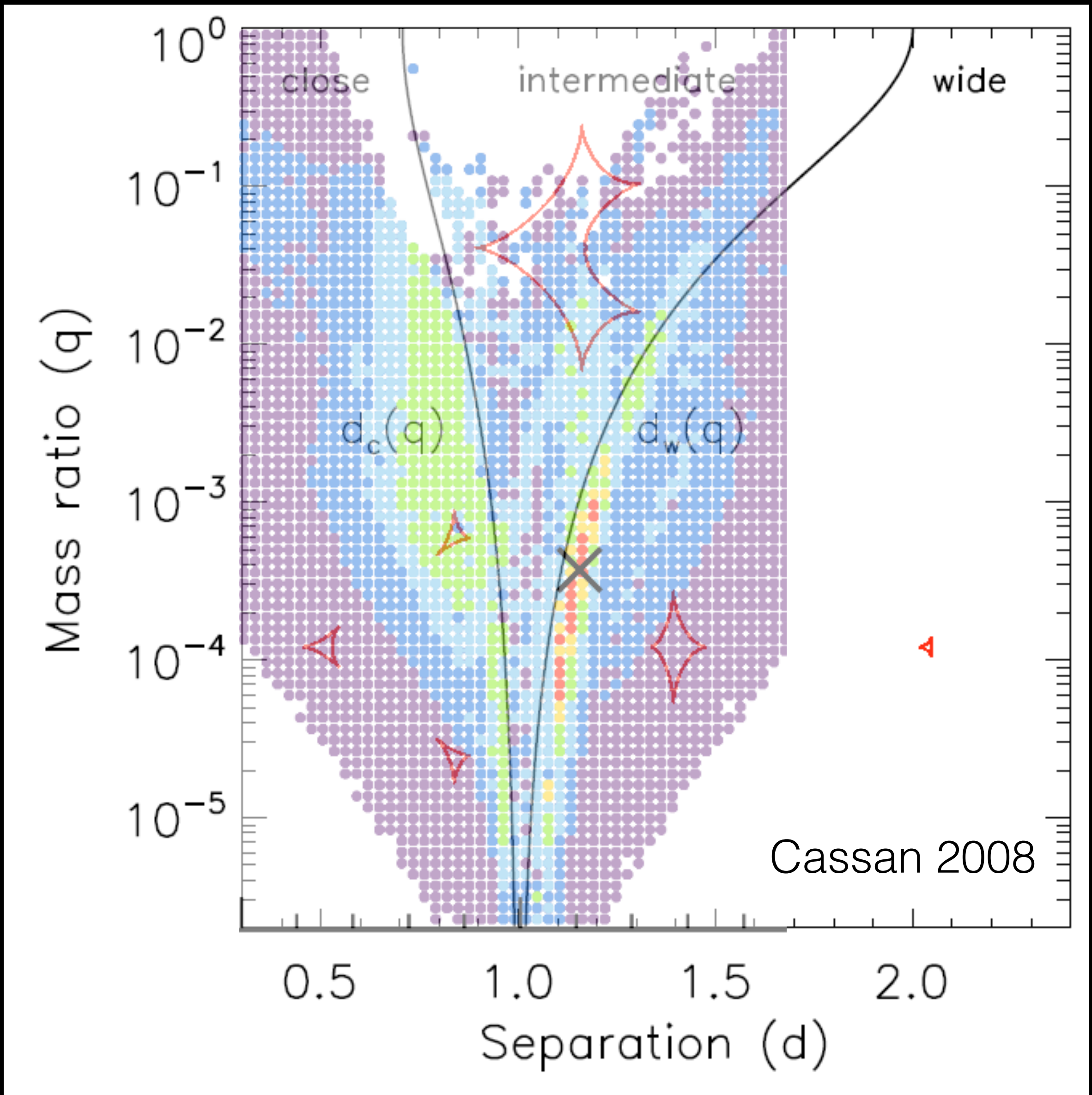

Actually have 3 separate models to fit to the data … which leads to multimodal likelihood spaces

Is it better to identify a single point as a best fit, or to integrate over the parameters for that model to identify most likely topology?

Model Comparison

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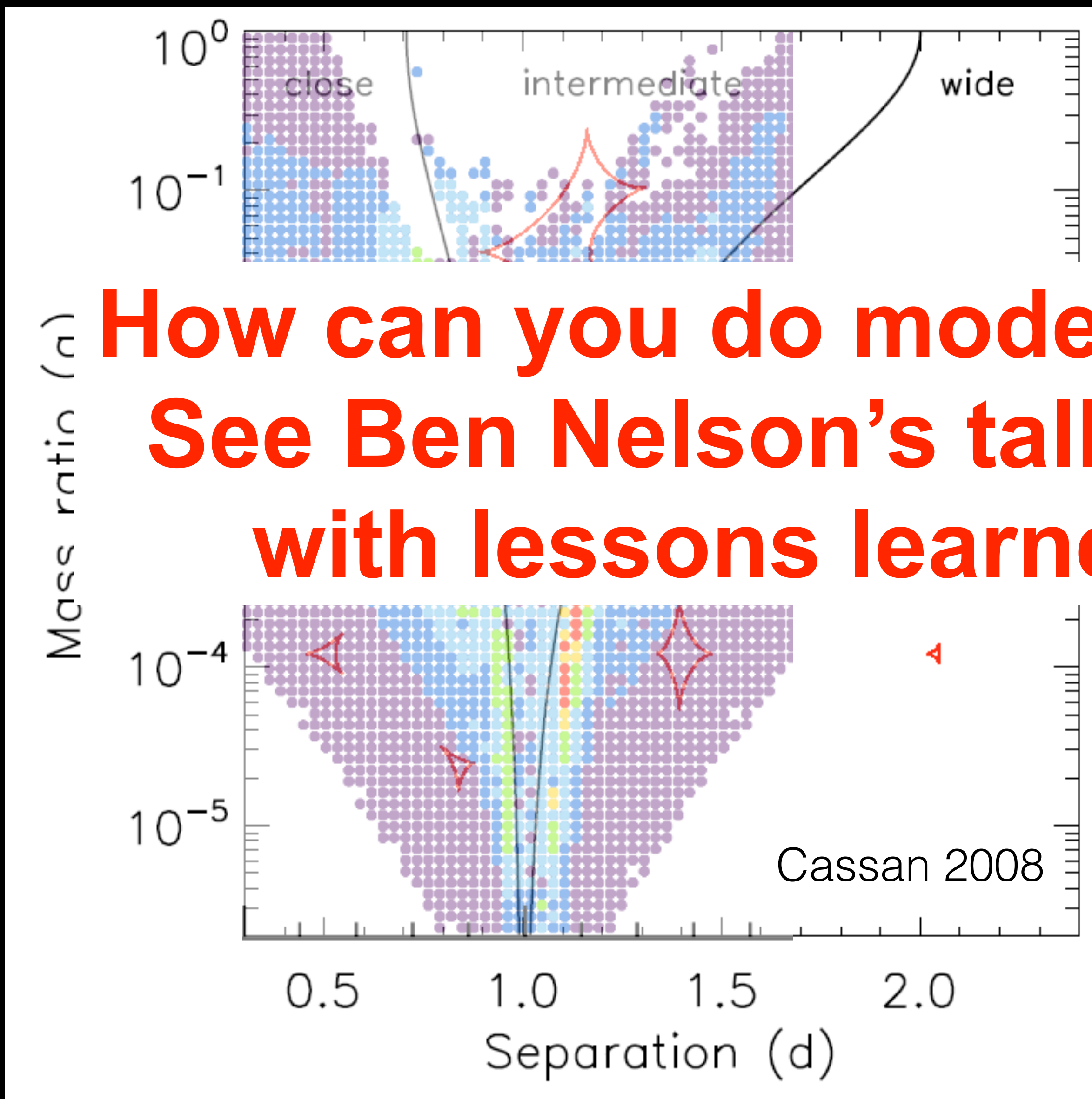

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a single point as a best fit, or to integrate over the parameters for that model to identify most likely topology?

How can you do model comparison? See Ben Nelson's talk on Saturday with lessons learned from RV.

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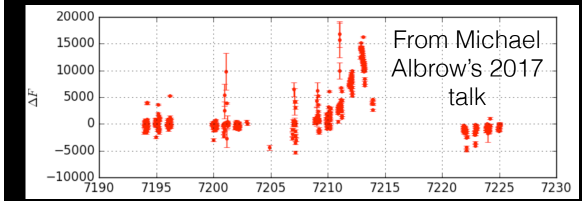

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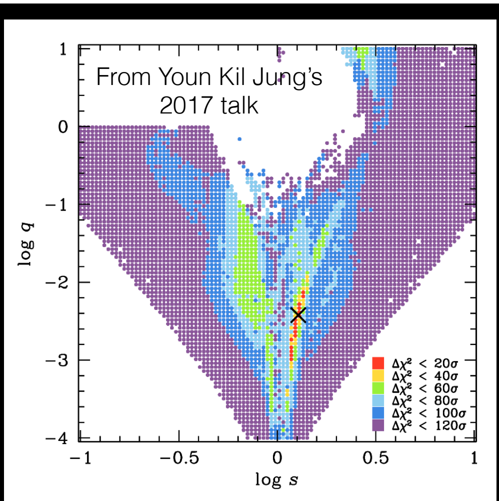

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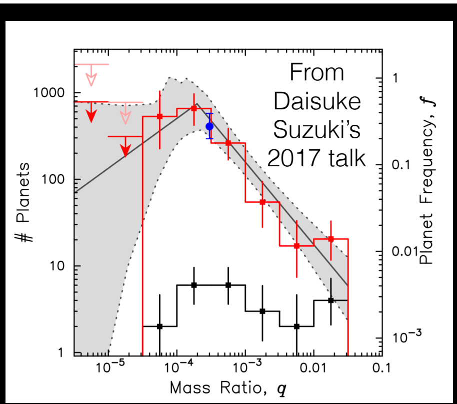

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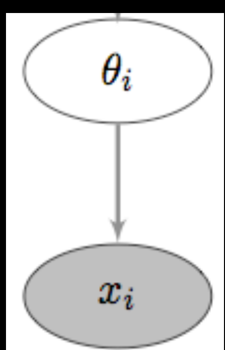
"Farther" from light curves (i.e. more model-centric)

Microlensing Populations

Within a Hierarchical Bayesian Framework

What do I mean?



Individual
Parameters

(likelihood → MCMC)

Observables

Microlensing Populations

Within a Hierarchical Bayesian Framework

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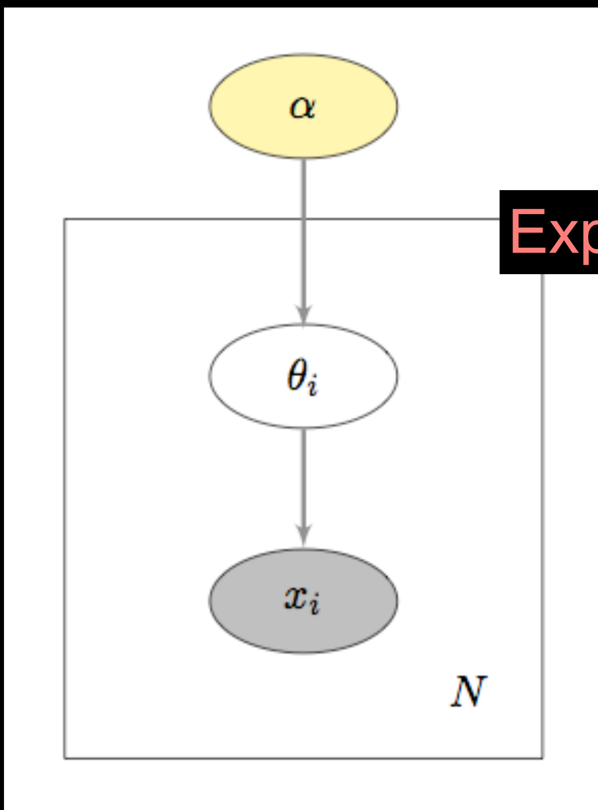

Population Parameters

Expand your likelihood!

Individual Parameters

Observables

Microlensing Populations

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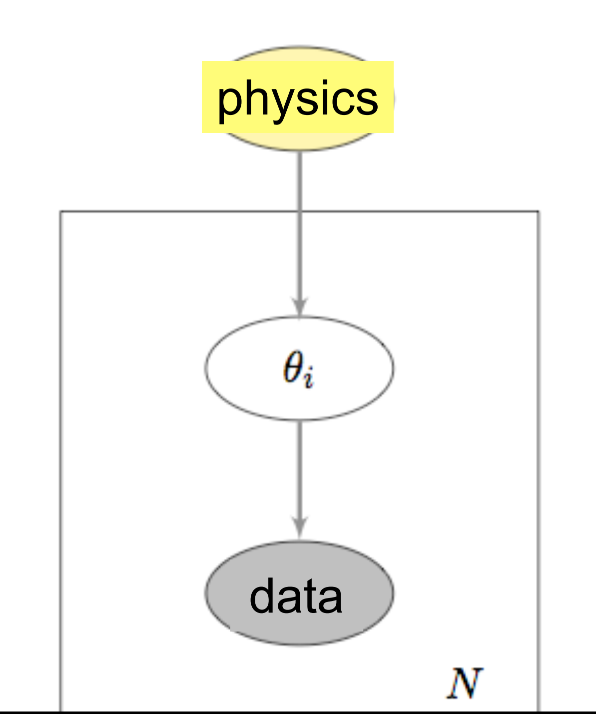

Population Parameters

Individual Parameters

Observables

Structure helps constrain posteriors:
Wolfgang & Lopez, 2015

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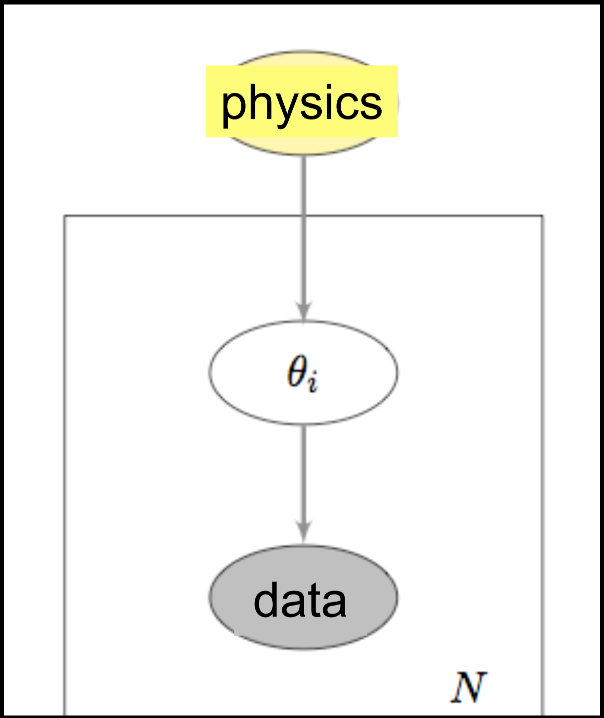

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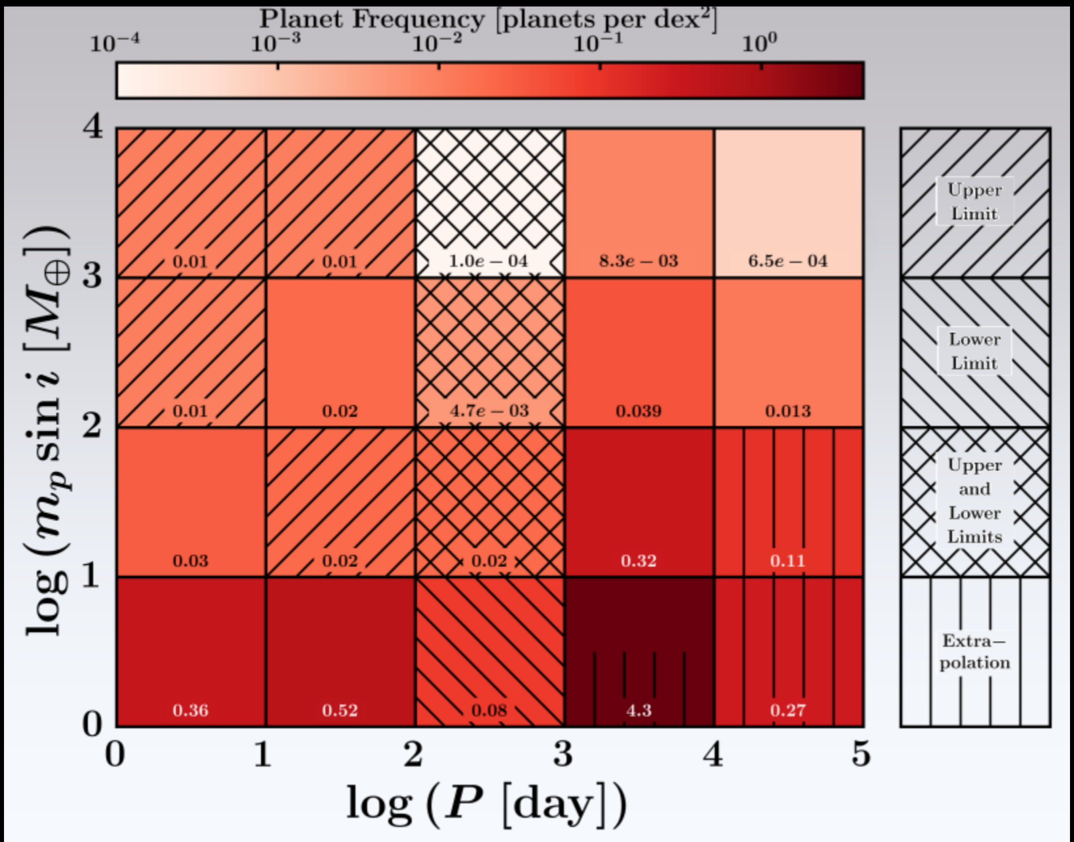
Why do we need it?

- Parameter **inference with uncertainties**
- Naturally deals with large measurement uncertainties and **upper limits**
- Can account for **selection effects** *within* the inference
- **Simultaneous posteriors** on individual and population parameters
- **Directly ties theory** to observations
- Framework for **model comparison**

Still use MCMC: “Just” adding another layer of probabilistic structure

Microlensing Populations

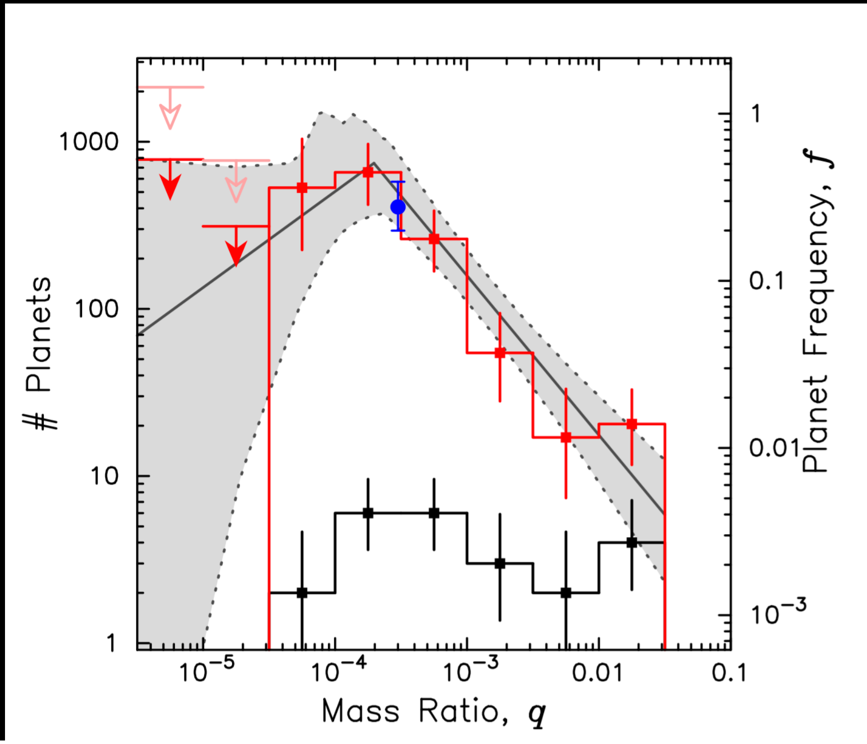
What would a hierarchical Bayesian framework add?



Clanton & Gaudi 2017

1) Uncertainties in population can easily and self-consistently incorporate uncertainties (including correlated) on μlensing, physical, *and* nuisance parameters

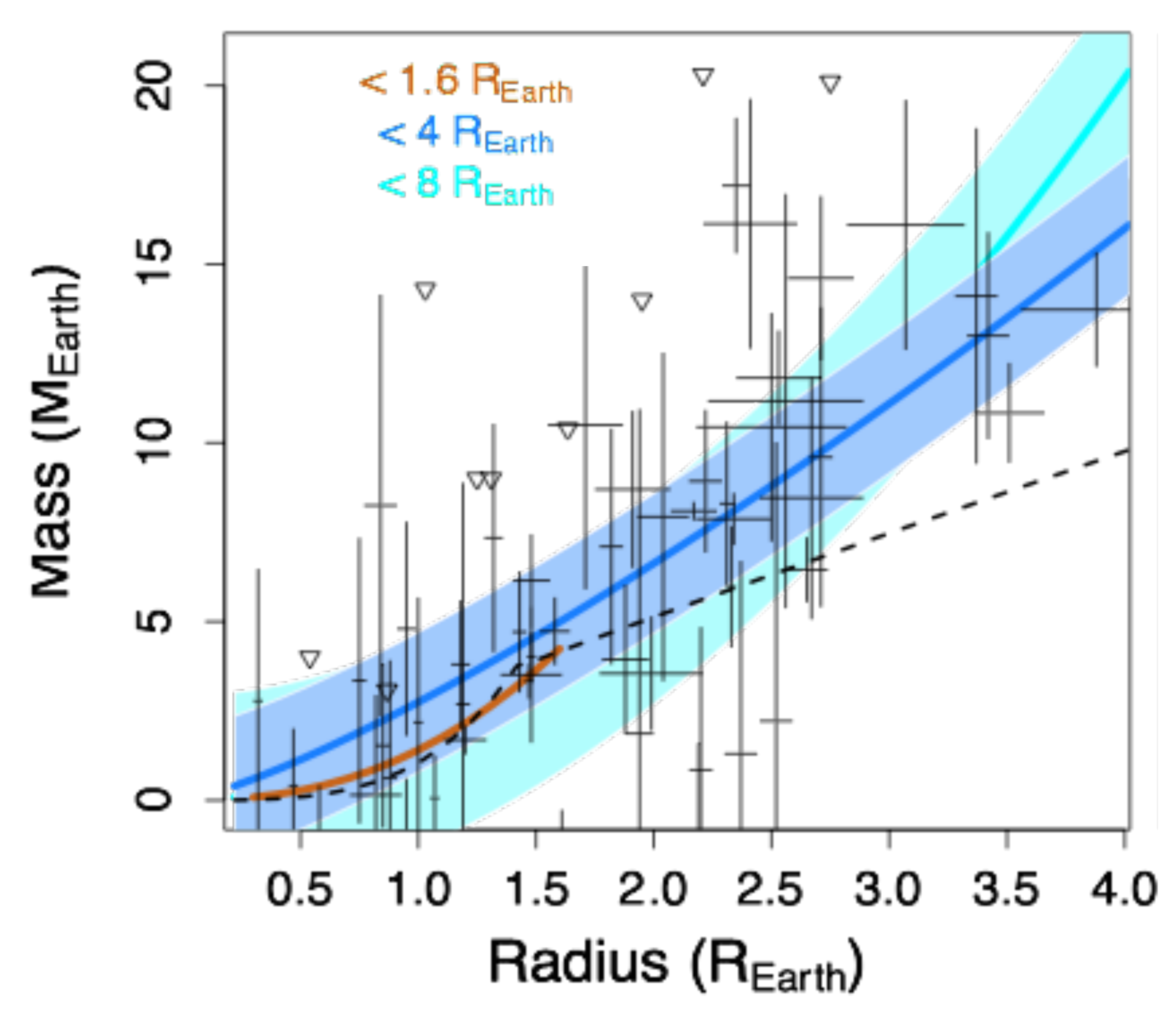
2) Can incorporate all degenerate solutions probabilistically.



Suzuki et al. 2017

Probabilistic Populations

Examples from Kepler (Wolfgang et al. 2015, 2016):
sub-Neptune compositions and mass-radius relations



Allows for a distribution of masses at a given radius as is motivated by observations and theory

Can distinguish between scatter due to measurement uncertainty and astrophysical scatter in the planet population

No binning necessary; also includes upper limits

Thank you - Thoughts?

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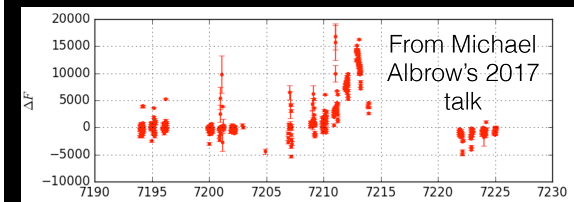

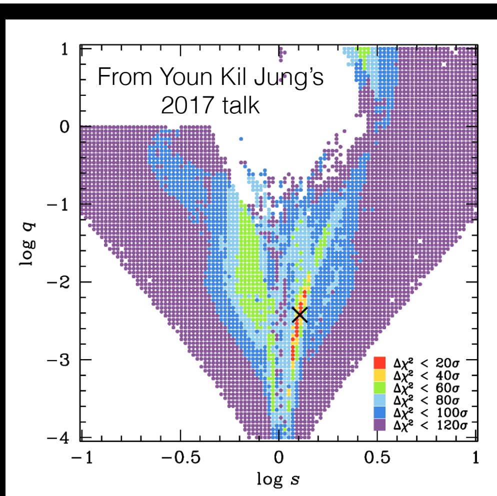

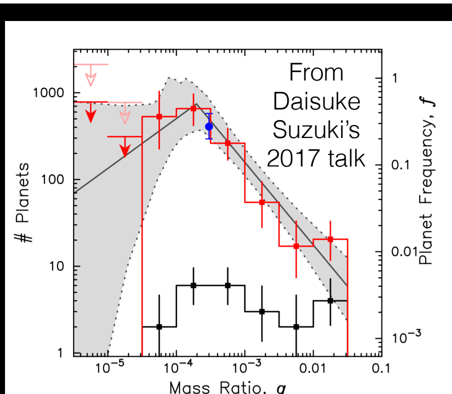

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