psst! go to:

aas233.dfm.io

how can new **Data Analysis Methods** *get more out of the* **Kepler/K2 Data?**

dan foreman-mackey
cca@flatiron // dfm.io // github.com/dfm

spoiler alert

by using
gradients

we can fit more
ambitious
models

everyone should learn about

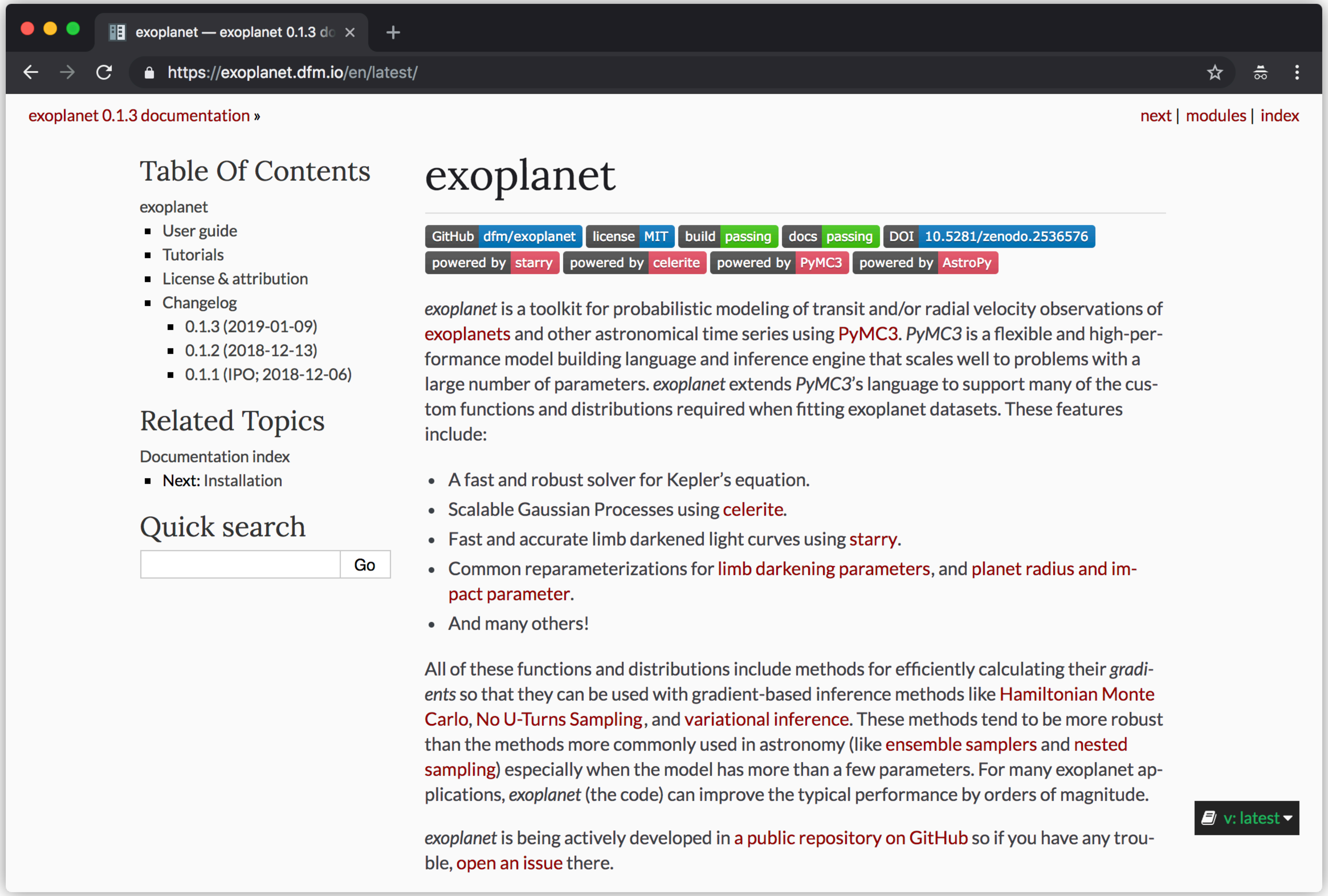
autodiff

and

hmc

* automatic differentiation & Hamiltonian Monte Carlo

exoplanet.dfm.io



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exoplanet

GitHub dfm/exoplanet | license MIT | build passing | docs passing | DOI 10.5281/zenodo.2536576

powered by starry | powered by celerite | powered by PyMC3 | powered by AstroPy

exoplanet is a toolkit for probabilistic modeling of transit and/or radial velocity observations of exoplanets and other astronomical time series using PyMC3. *PyMC3* is a flexible and high-performance model building language and inference engine that scales well to problems with a large number of parameters. *exoplanet* extends *PyMC3*'s language to support many of the custom functions and distributions required when fitting exoplanet datasets. These features include:

- A fast and robust solver for Kepler's equation.
- Scalable Gaussian Processes using celerite.
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- And many others!

All of these functions and distributions include methods for efficiently calculating their *gradients* so that they can be used with gradient-based inference methods like Hamiltonian Monte Carlo, No U-Turns Sampling, and variational inference. These methods tend to be more robust than the methods more commonly used in astronomy (like ensemble samplers and nested sampling) especially when the model has more than a few parameters. For many exoplanet applications, *exoplanet* (the code) can improve the typical performance by orders of magnitude.

exoplanet is being actively developed in a public repository on GitHub so if you have any trouble, open an issue there.

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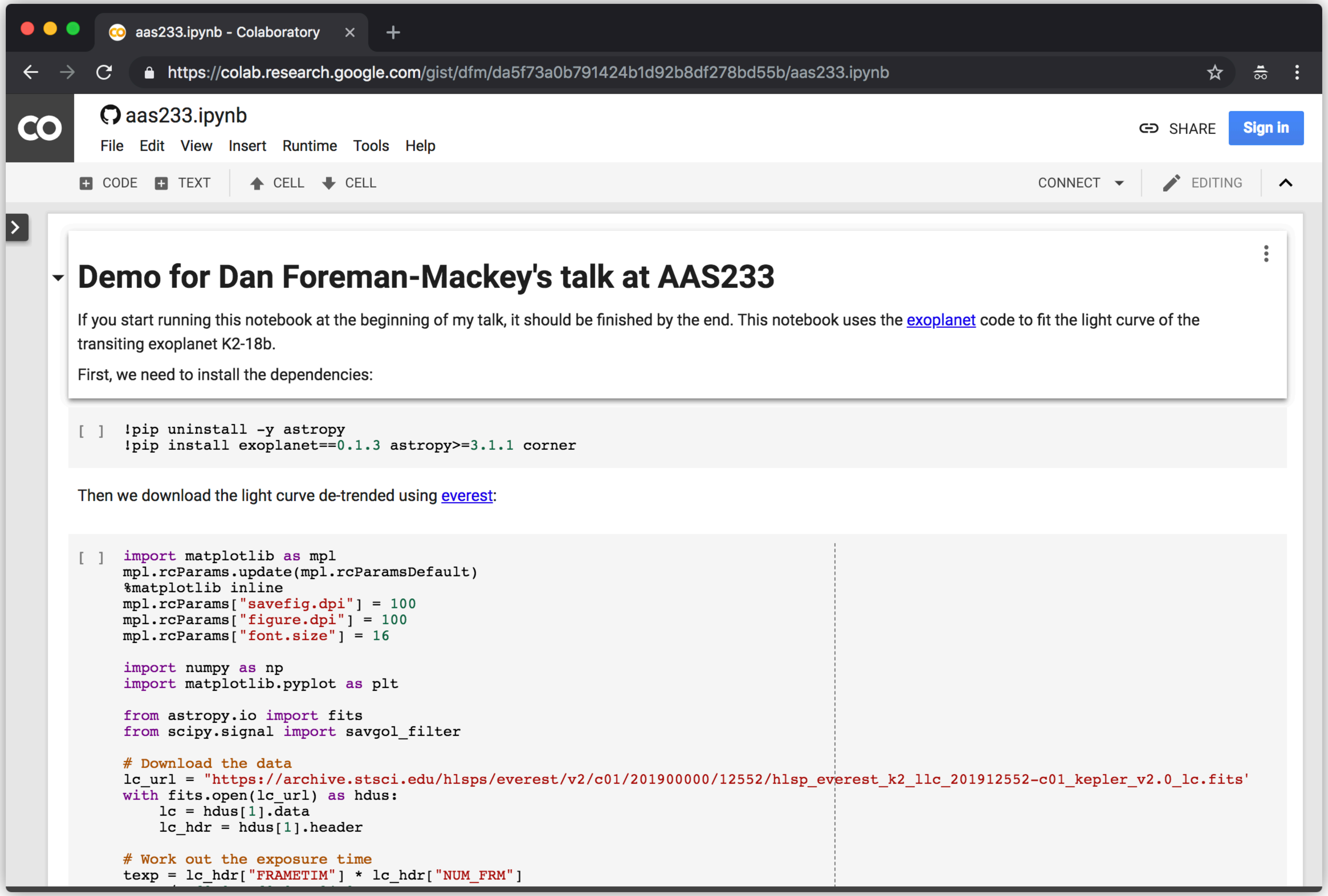


let's start with some **audience participation**

who here has…

heard of mcmc

?

who here has…

used mcmc

?

who here has…

heard of hmc

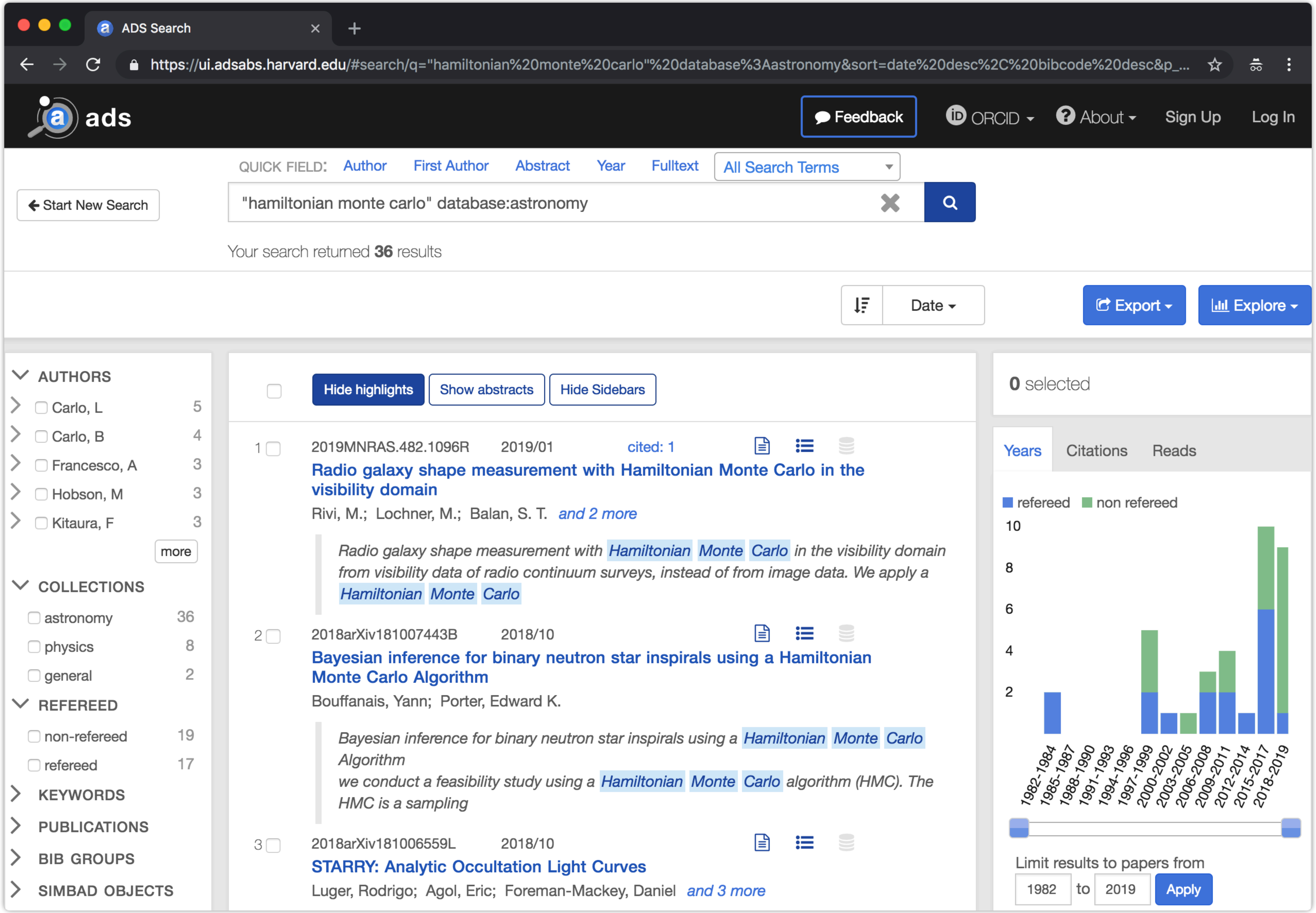
Hamiltonian Monte Carlo

?

who here has…

used hmc

?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QUICK FIELD:
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Year
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0 selected
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Reads
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non refereed
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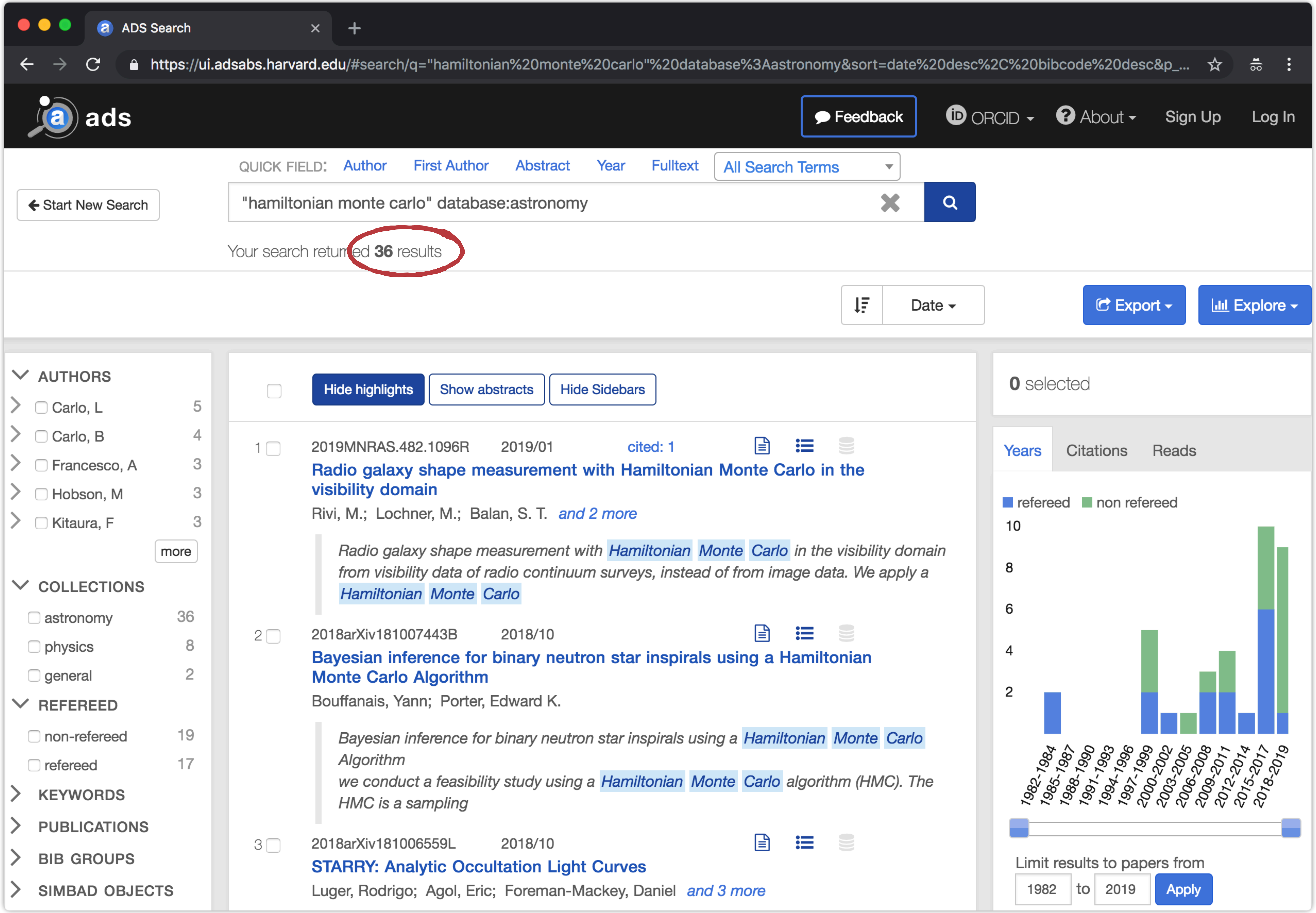
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Limit results to papers from
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how can new

Data Analysis Methods

get more out of the

Kepler/K2 Data?

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what is **data analysis** *anyways?*

the probability of
parameters
given some
data

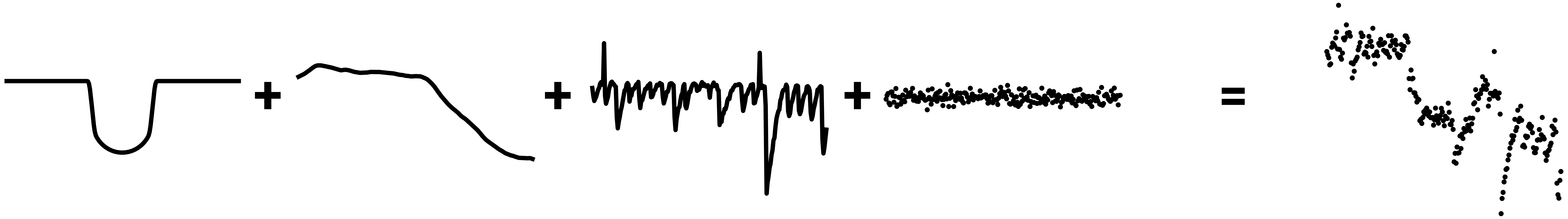
$$p(\mathrm{physics} \mid \mathrm{data})$$

we need a **model***

and a way to do **inference**

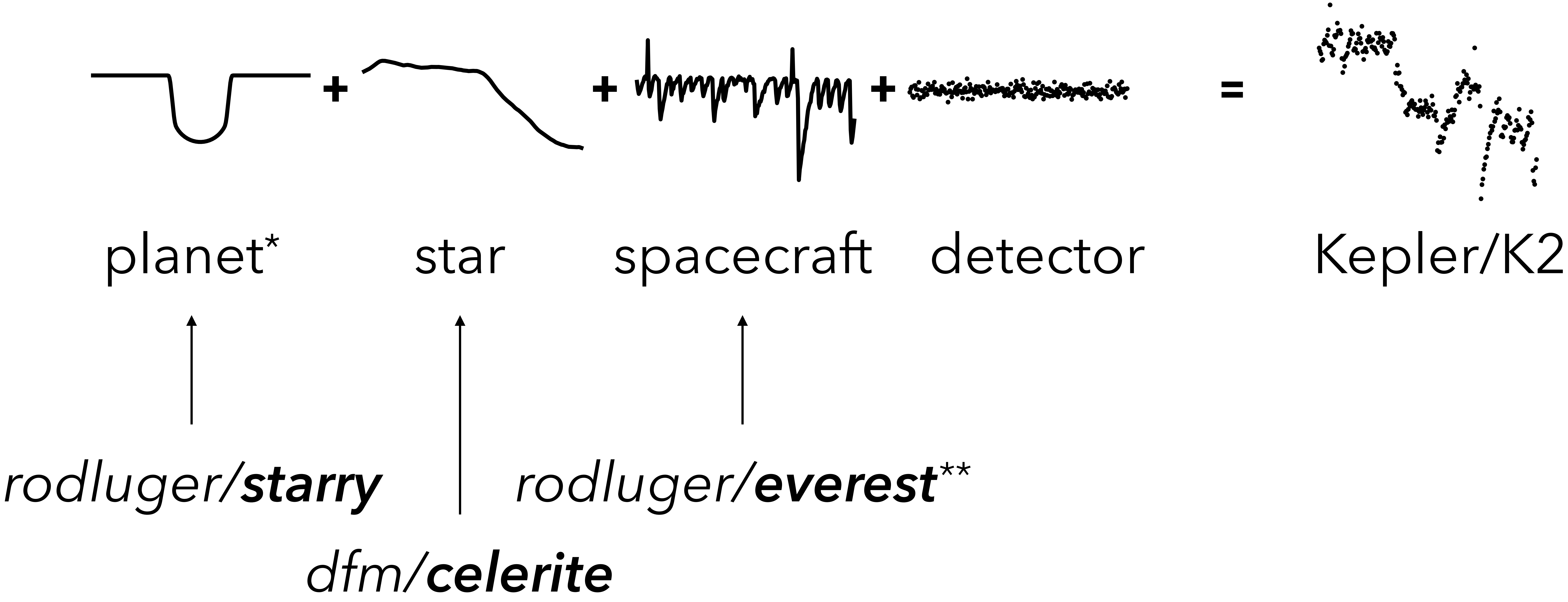
* & probably a way to evaluate it (efficiently?)

our **model**



* optional, of course

our **model**



* optional, of course

** these are all GitHub repositories

we need a **model***

and a way to do **inference**

* & probably a way to evaluate it (efficiently?)

"inference" is a fancy word for

fitting

in astronomy, we often use

mcmc

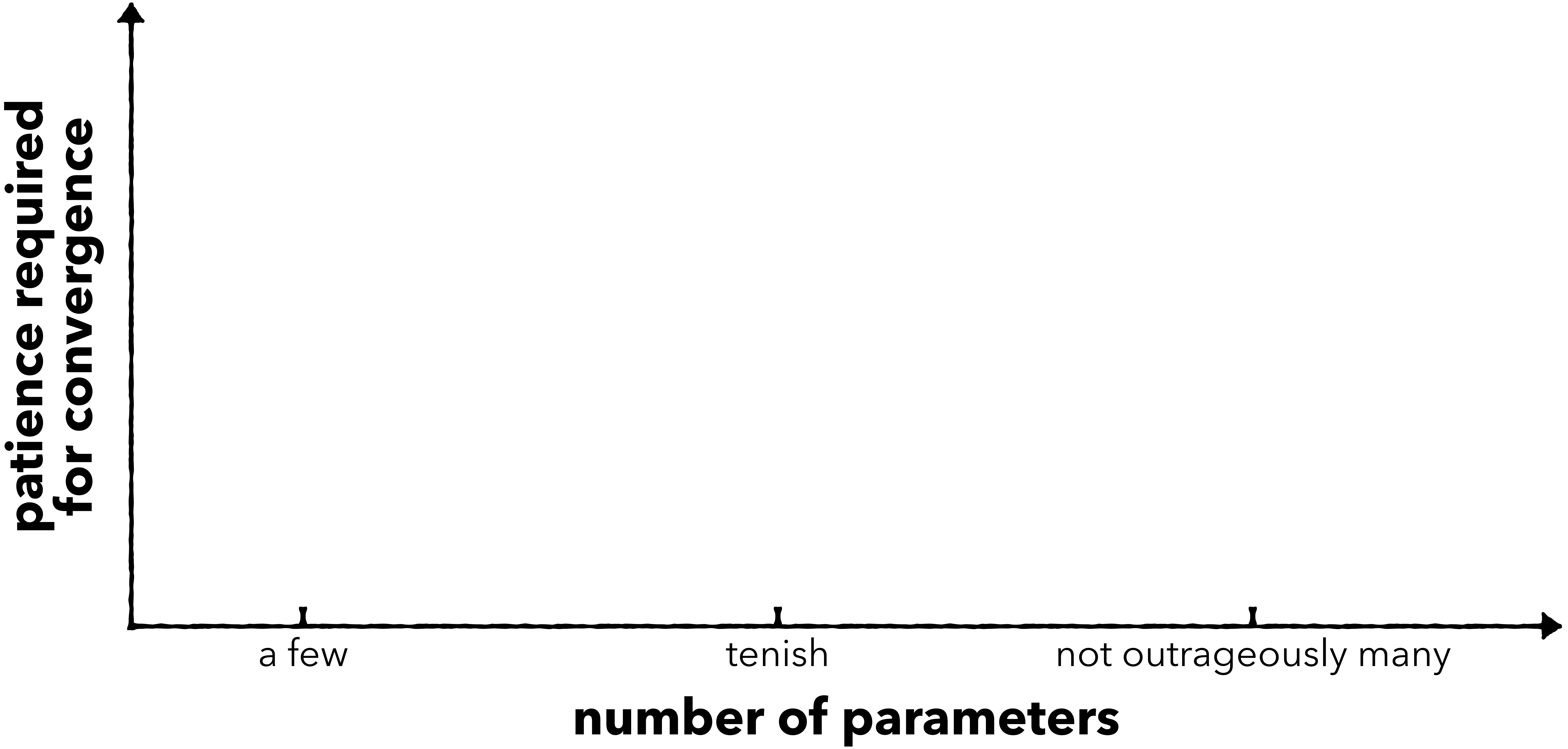
but

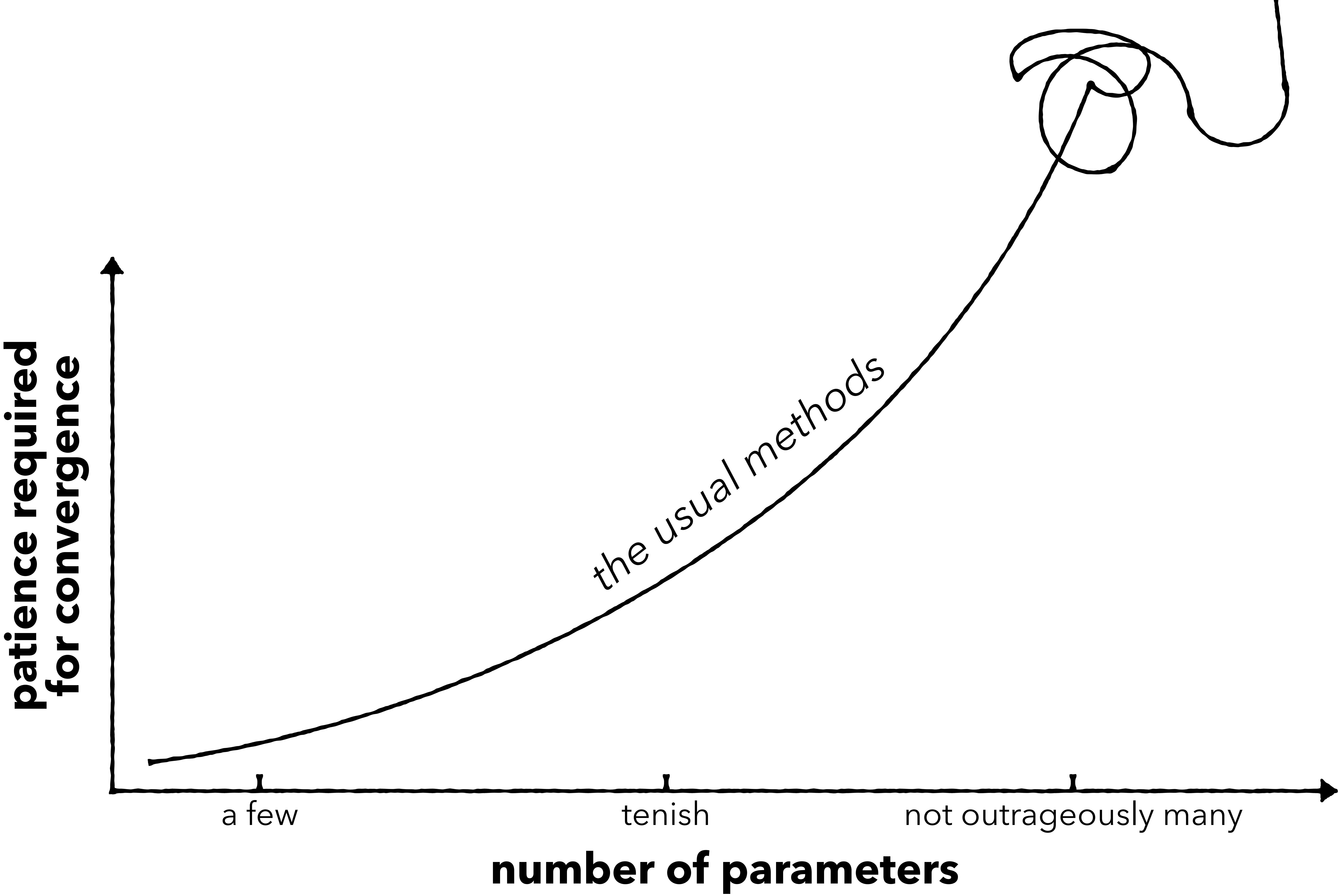
there are some problems

an incomplete list of reasons why the Inference Button™ might not Just Work

1. you have a lot of data
2. you have a lot of parameters
3. you have a lot of datasets
4. turns out inference is Hard*

* especially when you try to automate it


patience required
for convergence
a few
tenish
not outrageously many
number of parameters


patience required
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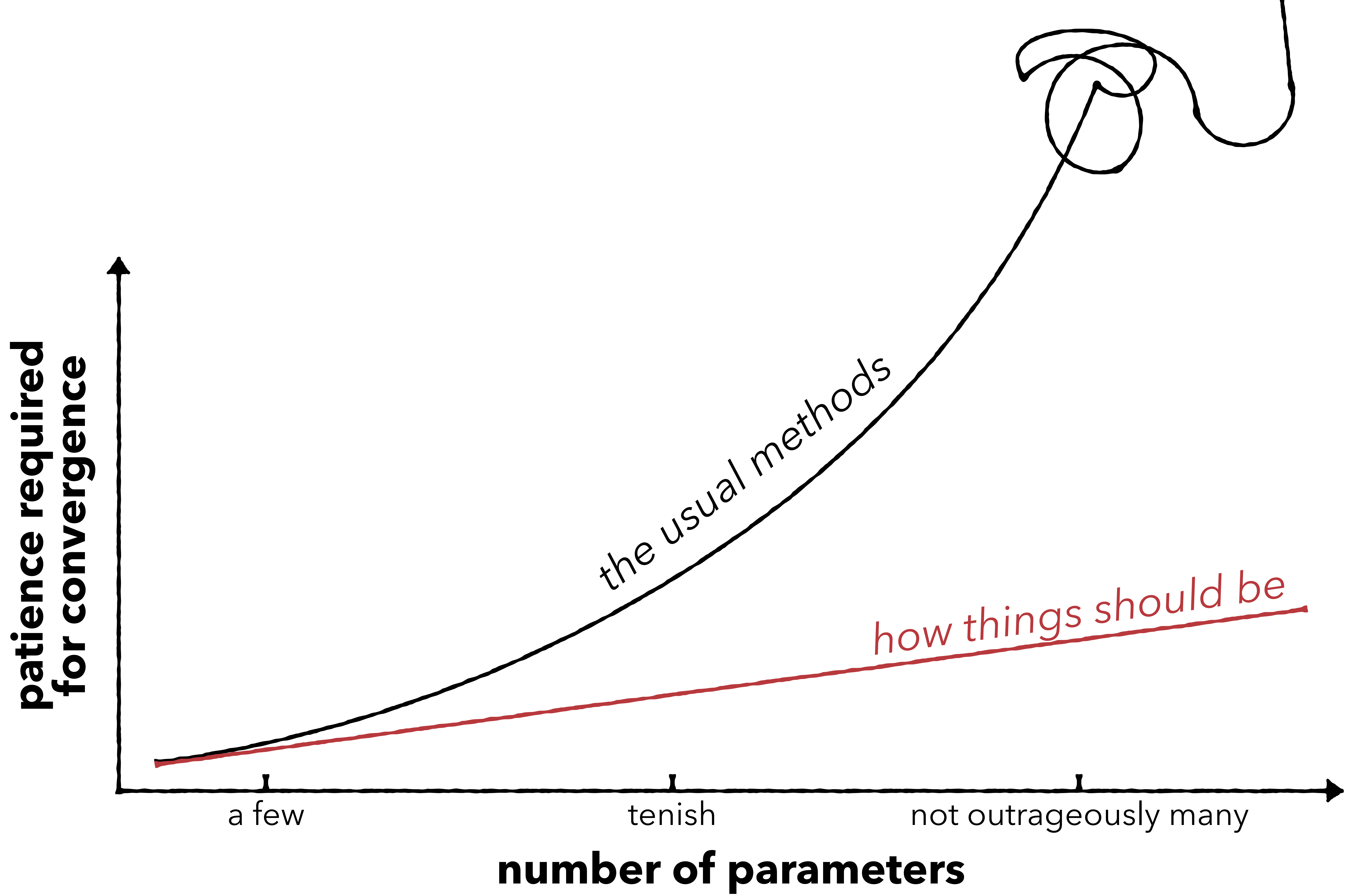

patience required for convergence
the usual methods
how things should be
a few
tenish
not outrageously many
number of parameters

the ultimate goal is to

reduce

the number of
model evaluations needed

Hamiltonian Monte Carlo

but hmc needs

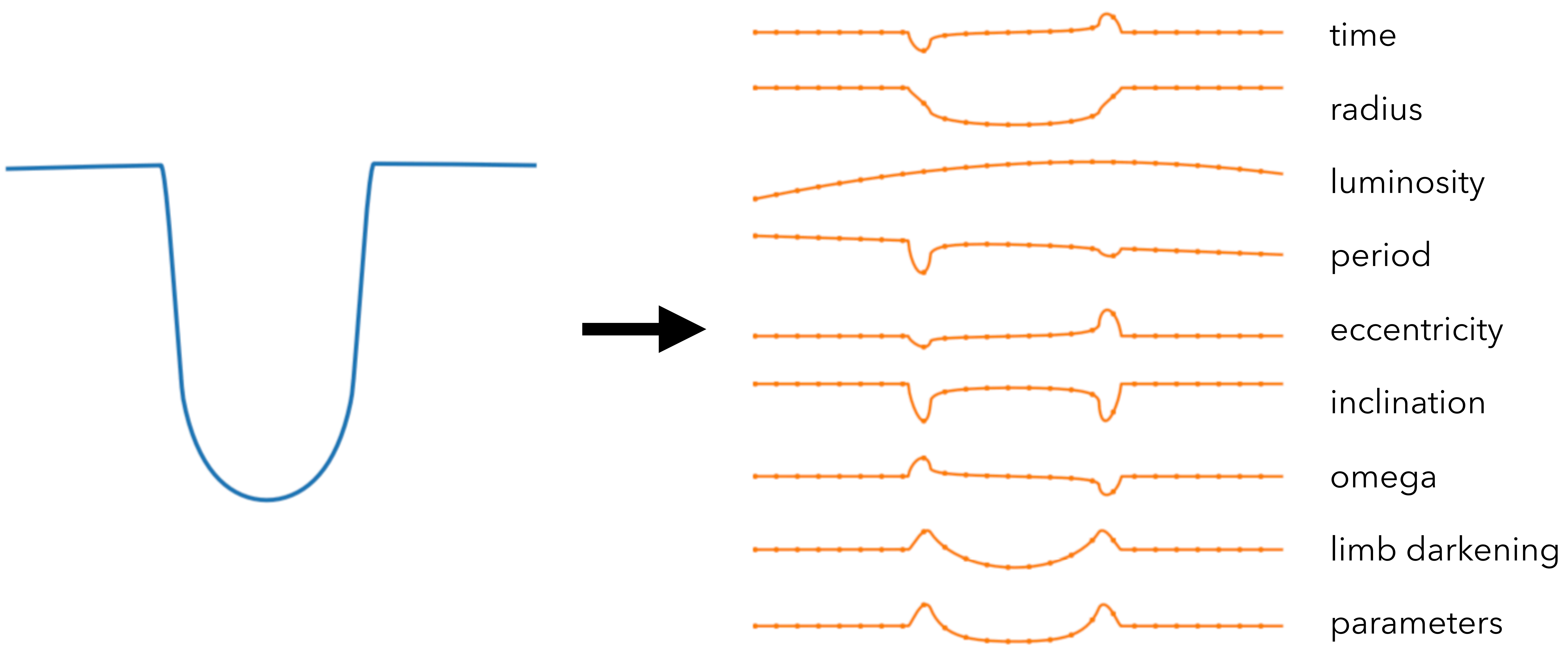
derivatives*

* not *those* derivatives

$$\frac{\mathrm{d}\,p(\mathrm{physics}\,|\,\mathrm{data})}{\mathrm{d}\,\mathrm{physics}}$$

transit light curve

derivative w.r.t.

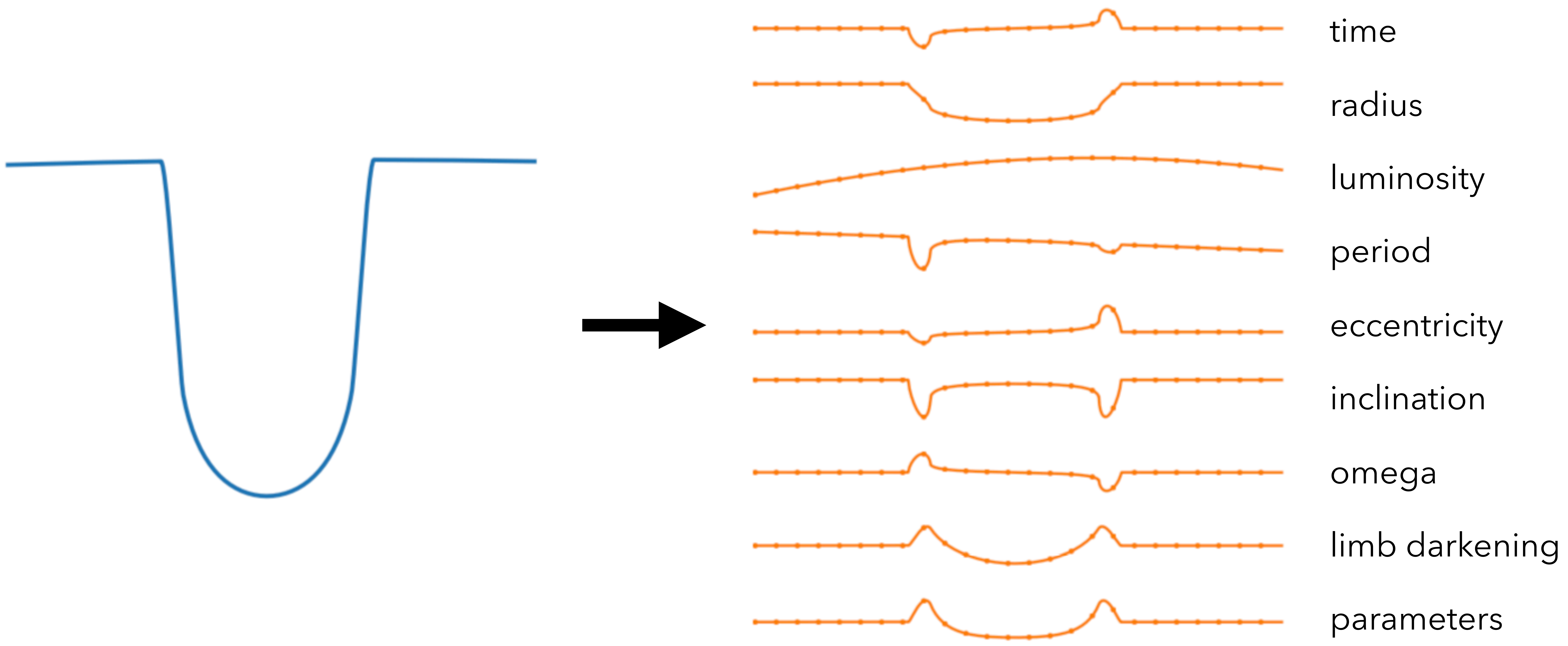


credit: Rodrigo Luger

computing all these
derivatives
doesn't sound
super fun

transit light curve

derivative w.r.t.



credit: Rodrigo Luger

automatic differentiation

* AKA "backpropagation"; AKA "the chain rule"

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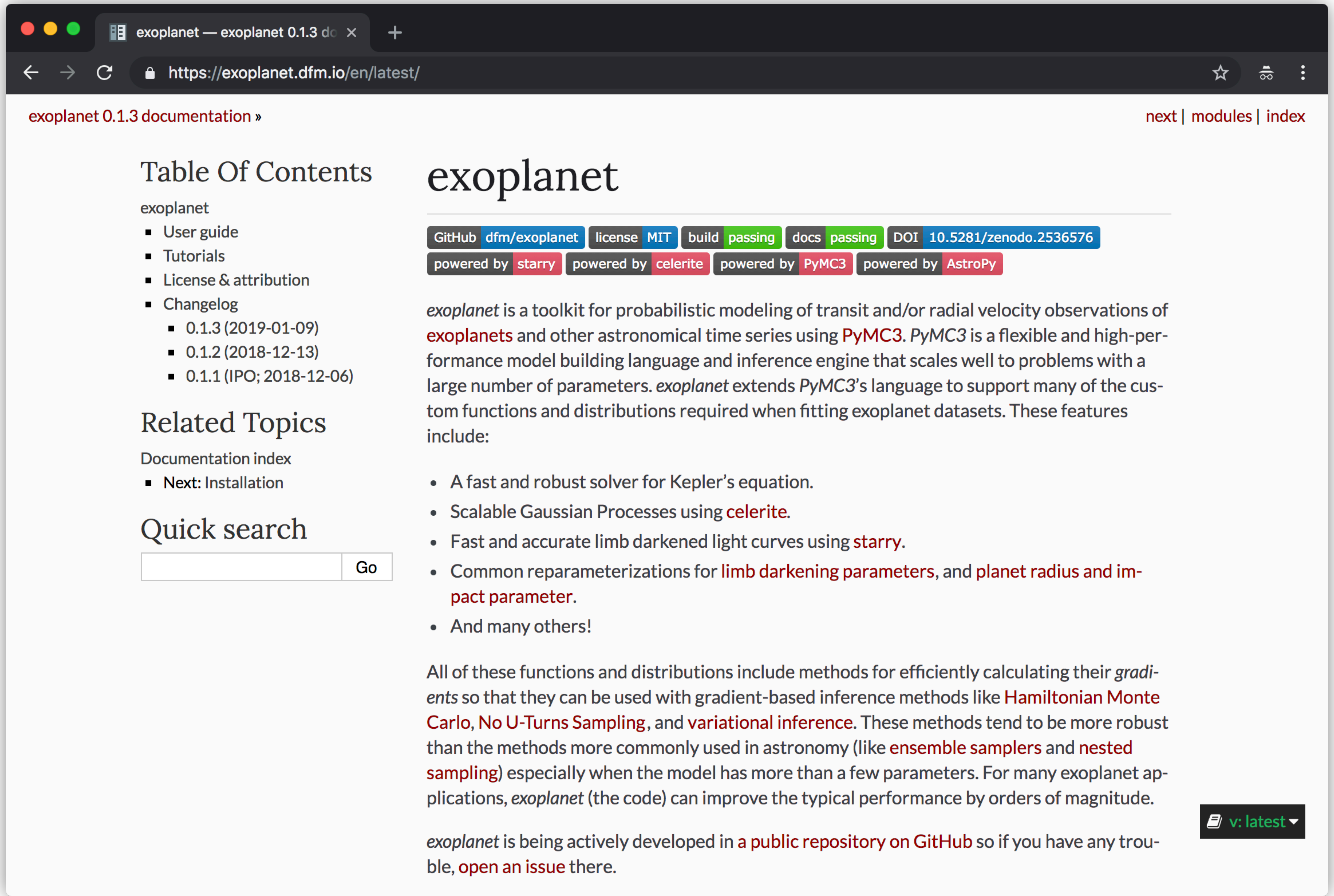

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powered by starry | powered by celerite | powered by PyMC3 | powered by AstroPy

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built on top of

PyMC3

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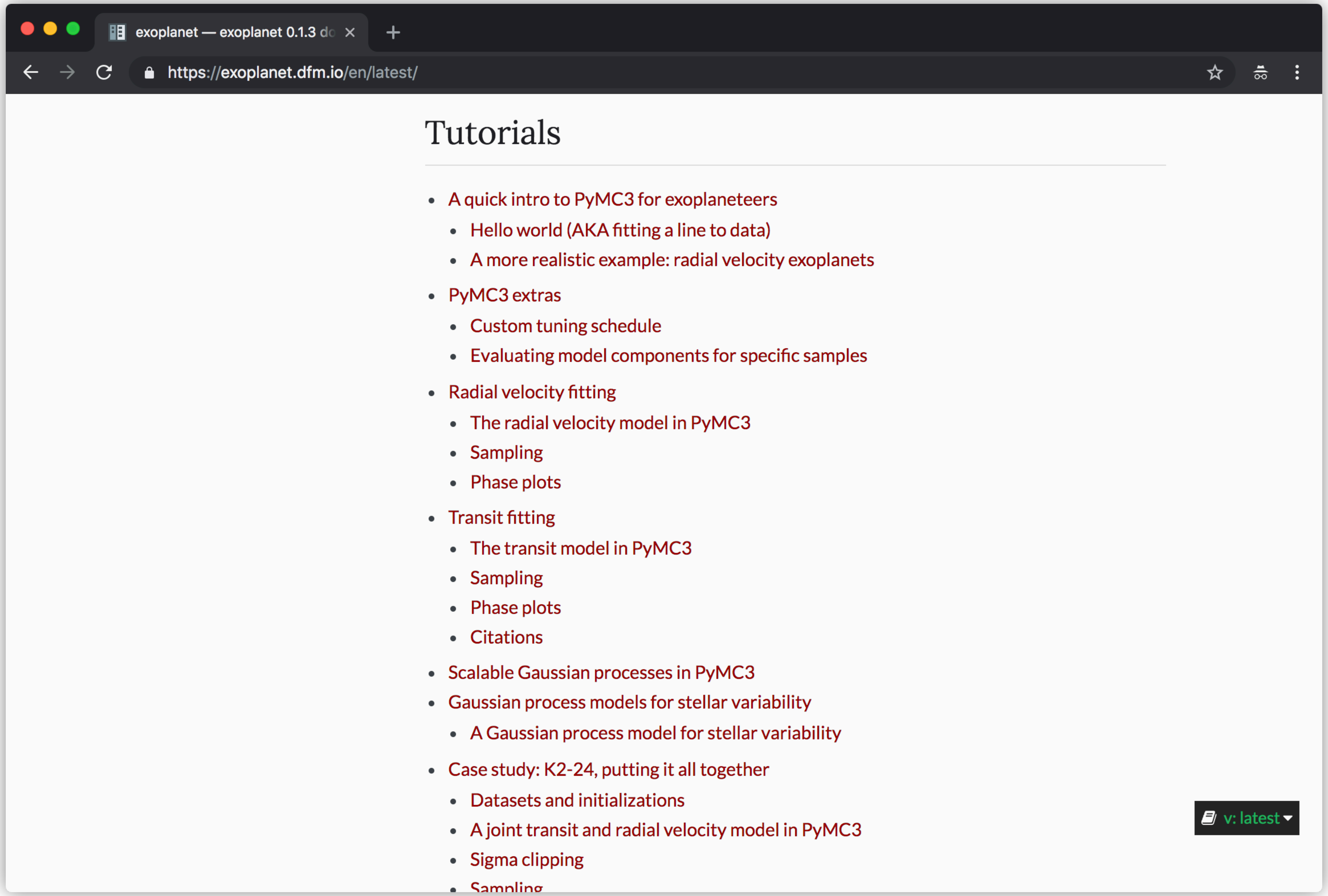

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Case study: K2-24, putting it a ×

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- **Next:** Fitting TESS data

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Note

This tutorial was generated from an IPython notebook that can be downloaded here.

Case study: K2-24, putting it all together

In this tutorial, we will combine many of the previous tutorials to perform a fit of the K2-24 system using the K2 transit data and the RVs from Petigura et al. (2016). This is the same system that we fit in the Radial velocity fitting tutorial and we'll combine that model with the transit model from the Transit fitting tutorial and the Gaussian Process noise model from the Gaussian process models for stellar variability tutorial.

Datasets and initializations

To get started, let's download the relevant datasets. First, the transit light curve from Everest:

```
import numpy as np
import matplotlib.pyplot as plt

from astropy.io import fits
from scipy.signal import savgol_filter

# Download the data
lc_url = "https://archive.stsci.edu/hlsps/everest/v2/c02/203700000/71098/hlsp_everest_k2_
with fits.open(lc_url) as hdus:
```

v: latest

exoplanet

is the plumbing for your

pipeline

it will help

you

get more out of the

Kepler/K2

data

exoplanet
has support for

1 multiplanet systems
2 RVs & transits
3 scalable gaussian processes
4 and much more

* and all the derivatives

exoplanet
is

1 robust
2 efficient
3 well tested
4 & well documented

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I can't wait to see what you build!

* PS how's your code doing?