
epos Documentation

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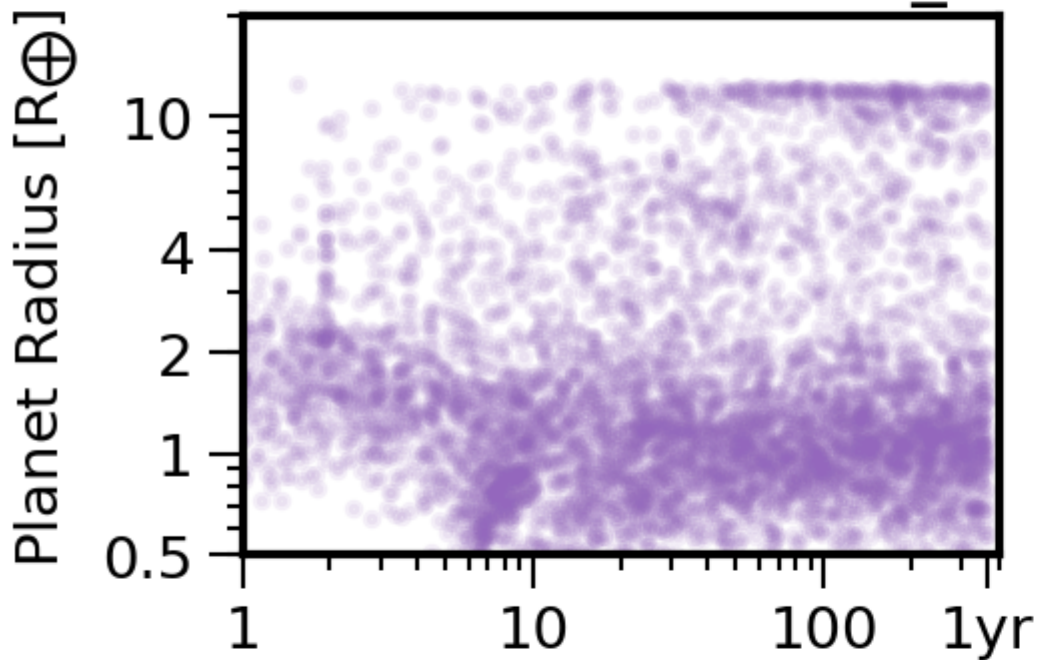
EPOS is a software package to simulate observations of exoplanet populations. It provides an interface between planet formation simulations and exoplanet surveys such as Kepler, accounting for detection biases in transit and radial velocity surveys.

Compare Planet Format

Forward Model

Apply Survey
Detection Bias

Formation Model: bern_n100



Inverse Model

Compare Intrinsic
Planet Population

CHAPTER 1

Applications

Use EPOS to calculate:

- Planet occurrence rates (*notebook*)
- Planet occurrence rate distributions (*notebook*)
- Planetary system architectures (*notebook*)
- Synthetic observations of planet formation models
- Survey biases of transit surveys other than Kepler (*notebook*)
- Planet populations in radial velocity surveys (*notebook*)
- Binned planet occurrence rates

CHAPTER 2

Install

EPOS is written in Python 3 and hosted on [github](#).

The quickest way to install epos is via pip:

```
pip install epospy
```


Familiarize yourself with the code is to take a look at the *Notebooks*

3.1 Installation

3.1.1 Pip

You can install epos with pip:

```
pip install epospy
```

Depending on your OS, you might have to use `sudo` or:

```
sudo -H pip install epospy
```

You should now be able to import the EPOS module into python:

```
>>> import EPOS
```

3.1.2 Github

Download the source from [github](https://github.com/GijsMulders/epos), preferably using git:

```
git clone https://github.com/GijsMulders/epos
```

You can then do a local install:

```
python setup.py sdist
sudo -H pip install -e .
```

In the future you can update to the latest version with:

```
git pull
```

3.1.3 Dependencies

EPOS has the following dependencies:

- python 3
- numpy 1.13+
- scipy
- matplotlib 2.0+
- astropy
- tqdm

The following software is required if you want to use the MCMC part of EPOS

- [emcee](#) for the MCMC fitting
- [corner.py](#) for the corner plots

`pip` should take care of these dependencies automatically but if you installed via `github` you will have to install them manually.

3.1.4 Testing

The quickest way to test EPOS is by running the *Notebooks* locally.

To test the basic functionality of EPOS, you can also run the test scripts. First, copy the test and example scripts to a local directory:

```
>>> import EPOS
>>> EPOS.scripts.install()
```

Navigate to the scripts directory (`epos-scripts/tests/`) and run each of:

```
./test_1_survey.py
./test_2_montecarlo.py
./test_3_mcmc.py
./test_4_multicore.py
./test_5_occurrence.py
```

If you don't have `ipython` installed, you can also run `python test_1_survey.py` or copy-paste the script into a terminal.

Each command is described in the comments, and provides an introduction to the basic functionality.

3.2 Examples

Please take a look at the *Notebooks*

There are also a number of example scripts included that demonstrate different functionality. The scripts contains comments describing each command. These scripts are copied to the `epos-scripts/examples/` directory by `EPOS.scripts.install()`.

3.2.1 Parametric mode

The first example shows how to fit a parametric function in planet radius and orbital period to Kepler data. The script can be run with:

```
./example_1_parametric_mode.py
```

Here, is a step-by-step description of each set of commands. First, load EPOS and set the output directory name

```
>>> import EPOS
>>> epos = EPOS.epos(name='example_1')
```

Second, load the observations (Kepler DR25 planet candidate list) and survey detection efficiency

```
>>> obs, survey = EPOS.kepler.dr25(Huber=True, Vetting=True, score=0.9)
>>> epos.set_observation(**obs)
>>> epos.set_survey(**survey)
```

Next, define the parametric distribution function that will be fitted to the data. (The example is a broken power-law in both the planet size and distance dimension from `fitfunctions.py`, but you can define your own)

```
>>> epos.set_parametric(EPOS.fitfunctions.brokenpowerlaw2D)
```

Now initialize the fit parameters with their initial values and limits (min, max). The first parameter is the normalization, defined as the number of planets per star over the simulated radius-period range:

```
>>> epos.fitpars.add('pps', 2.0, min=0)
```

The next six parameters (one break point and two indices for each dimension) control the shape of the period-radius distribution

```
>>> epos.fitpars.add('P break', 10., min=2, max=50, is2D=True)
>>> epos.fitpars.add('a_P', 1.5, min=0, is2D=True)
>>> epos.fitpars.add('b_P', 0.0, dx=0.1, is2D=True)
>>> epos.fitpars.add('R break', 3.0, min=1.0, max=5, is2D=True)
>>> epos.fitpars.add('a_R', 0.0, dx=0.1, is2D=True)
>>> epos.fitpars.add('b_R', -4., fixed=True, is2D=True)
```

Note that the last parameter is fixed and thus not fitted for. `dx` is a parameter that controls the initial distribution of walkers when the initial value is zero.

Next, define the simulation range.

```
>>> epos.set_ranges(xtrim=[0, 730], ytrim=[0.3, 20.], xzoom=[2, 400], yzoom=[1, 6], Occ=True)
```

For transits, `x` refers to orbital period and `y` refers to planet size. The simulated range is that supplied by the detection efficiency grid and trimmed (`trim`) to the given values. For the observational comparison we `zoom` in a bit further.

Now we're ready to go! Run the code once with the initial values:

```
>>> EPOS.run.once(epos)
```

Then run the mcmc chain

```
>>> EPOS.run.mcmc(epos, nMC=1000, nwalkers=100, nburn=200, threads=20, Saved=True)
```

This runs multi-core with 20 threads. `Saved` indicates whether the mcmc will be skipped if a previously saved chain is present on disk. `Saved=False` always reruns the chain.

Define a set of bins where planet occurrence rates are calculated, both from the data and from integrating the fitted planet distributions, and calculate all the rates

```
>>> epos.set_bins(xbins=[[2,400],[0.9*365,2.2*365]], ybins=[[1,6],[0.7,1.5]]) # eta_
↳ zoom, eta_earth
>>> EPOS.occurrence.all(epos)
```

Last, plot everything.

```
>>> EPOS.plot.survey.all(epos)
>>> EPOS.plot.input.all(epos)
>>> EPOS.plot.output.all(epos)
>>> EPOS.plot.mcmc.all(epos)
>>> EPOS.plot.occurrence.all(epos)
```

Plots will appear in the png/example_1/ subfolder

3.2.2 Multi-planet Mode

```
./example_2_multiplanet_mode.py
```

In multi-planet mode, the first planet in the system is drawn from a parametric distribution same as above. However, we adjust the initial guess for the slope after the period break

```
>>> epos.fitpars.add('b_P', -1, max=1, dx=0.1, is2D=True)
```

Next we tell epos to draw additional planets in the system assuming the spacing between adjacent planets is drawn from a dimensionless distribution:

```
>>> epos.set_multi(spacing='dimensionless')
```

We generate 10 planets per system.

```
>>> epos.fitpars.add('npl', 10, fixed=True)
```

The fit parameters for the dimensionless distribution are:

```
>>> epos.fitpars.add('log D', -0.3)
>>> epos.fitpars.add('sigma', 0.2, min=0)
```

Other properties of the planetary systems can also be fit for (or not):

```
>>> epos.fitpars.add('dR', 0.01, fixed=True) # Dispersion in planet radii
>>> epos.fitpars.add('inc', 2.0) # mode of mutual inclinations
>>> epos.fitpars.add('f_iso', 0.4) # Fraction of isotropic systems
>>> epos.fitpars.add('f_cor', 0.5, fixed=True) # Correlated noise
```

Then proceed as in single-planet mode.

3.2.3 Planet Formation Mode

Example 3 is a template for using EPOS with a planet formation / population synthesis model.

```
./example_3_population_synthesis.py
```

Generate some random data in the same format as the outcome of a planet formation model. (These are 77 systems with 8 planets each)

```
>>> n= 616
>>> sma= 10.**np.random.uniform(-1.3,1,n)
>>> mass= 10.** (3.*np.random.power(0.5, n))
>>> radius= 10.** np.random.power(0.5, n)
>>> inc= np.random.rayleigh(2, n)
>>> starID= np.repeat(np.arange(n/8), 8)
```

Load the planet formaton model into EPOS as a dictionary:

```
>>> pfm= {'sma':sma, 'mass':mass, 'radius':radius, 'inc':inc, 'starID':starID}
>>> epos.set_population('Planet Formation Model', **pfm)
```

Set 1 in 5 stars to have planetary systems

```
>>> epos.fitpars.add('eta', 0.2, isnorm=True)
```

Optionally, use a mass-radius relation if the model does not simulate planetary radii:

```
>>> epos.set_massradius(EPOS.massradius.CK17, 'Chen & Kipping 2017', masslimits=[0.1,
↪100])
```

Define a polygonic bin for mini-Neptunes

```
>>> xmin, xmax= 3, 200
>>> ymin, ymax= 1.2, 4
>>> xb, yb= 100, 2.2
>>> xyMN= [[xmin,ymax],[xmax,ymax],[xmax,ymin], [xb,ymin], [xmin,yb]]
>>> epos.set_bins_poly([xyMN],
    labels=['Mini-\nNeptunes'])
```

Then run epos and save/plot as usual

```
>>> EPOS.run.once(epos)
>>> EPOS.occurrence.all(epos)
>>> EPOS.plot.survey.all(epos)
>>> EPOS.plot.input.all(epos, imin=1e-4, color='C8')
>>> EPOS.plot.occurrence.all(epos, color='C8', alpha_fac=50.)
>>> EPOS.plot.output.all(epos, color='C8')
```

3.2.4 Radial Velocity Surveys

Example 5 shows how to estimate the distribution of planets from a radial velocity survey:

```
./example_5_radial_velocity.py
```

Two commands are different from fitting a transit survey: First, tell epos that we are doing a radial velocity survey (RV=True), that we are not doing the Monte Carlo simulation (MC=False) and that we are fitting for the planet mass distribution (Msini=True)

```
>>> epos= EPOS.epos(name='example_5', RV=True, MC=False, Msini=True)
```

Second, we define the radial velocity survey data, here from Mayor+ 2011

```
>>> obs, survey= EPOS.rv.Mayor2011()
>>> epos.set_observation(**obs)
>>> epos.set_survey(**survey)
```

3.3 FAQ

3.3.1 Frequently asked questions

If you have any difficulties or questions running EPOS that are not addressed in the documentation or FAQ please contact gdmulders@gmail.com

I'm getting an `AttributeError: 'module' object has no attribute 'geomspace'`

Please upgrade to numpy 1.13 or a more recent version

3.4 Notebooks

3.4.1 Examples

- *Occurrence Rates* (save to disk)
- *Parametric Mode* (save to disk)
- *Multi-planet Mode* (save to disk)
- *Custom exoplanet survey* (save to disk)

The notebooks are also viewable on [github](#)

3.4.2 Papers

- Mulders+ 2018 (see tutorials *Parametric Mode* and *Multi-planet Mode*)
- Fernandes+ 2019
- Mulders+ 2019 (in prep)

These script are are also viewable on [this github folder](#) and you can copy these scripts to a local directory with:

```
>>> import EPOS
>>> EPOS.scripts.install()
```

3.5 Occurrence Rates

Estimate planet occurrence rates using the inverse detection efficiency method.

This example calculates the occurrence rates for different classes of planets, defined by a size and period-range

```
[1]: import EPOS
import numpy as np
import matplotlib.pyplot as plt
```

initialize the EPOS class with the kepler dr25 exoplanet survey

```
[2]: epos= EPOS.epos(name='occurrence_rate_inverse', survey='Kepler')
```

```
|~| epos 3.0.2 |~|

Initializing 'occurrence_rate_inverse'

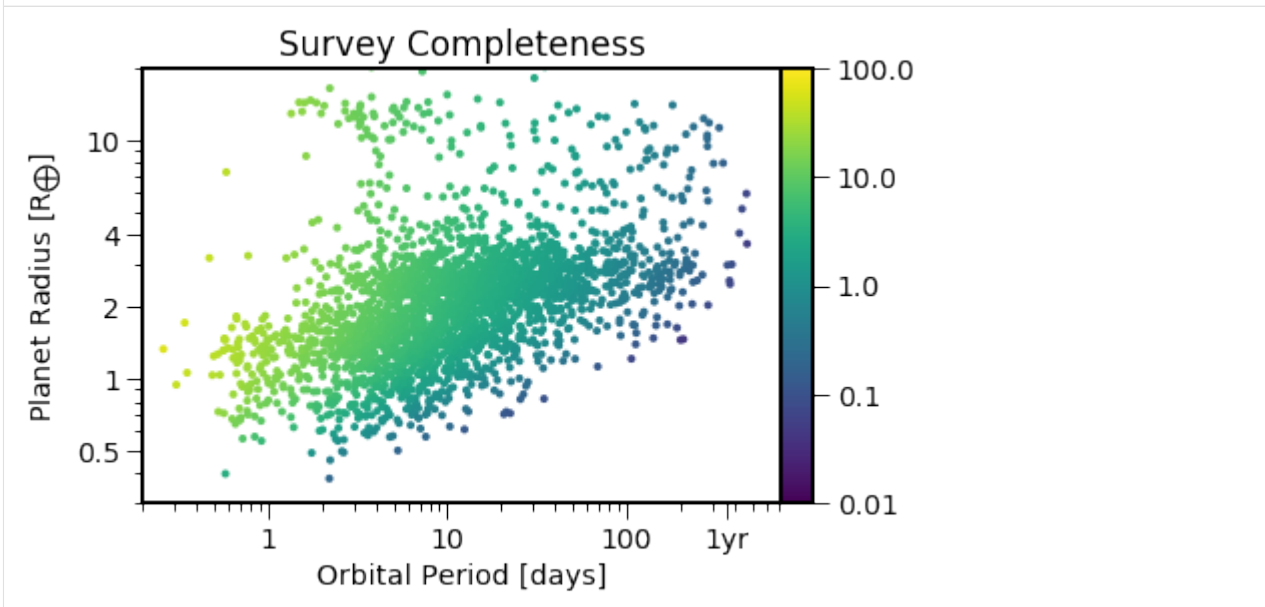
Using random seed 1678722249

Survey: Kepler-Gaia all dwarfs, reliability > 0.9
```

Calculate the survey completeness for each planet

```
[3]: EPOS.occurrence.planets(epos)
EPOS.plot.occurrence.colored(epos, NB=True)
```

Interpolating planet occurrence



Define a set of period (x) and radius (y) bins to calculate occurrence rates for Hot Jupiters, Super Earths, and Mini-Neptunes

```
[4]: # Hot-Jupiters
Period_HJ= [1,10] # days
Radius_HJ= [8,16] # earth radii
# super-earths
Period_SE= [0.5,50] # days
Radius_SE= [0.7,1.8] # earth radii
# mini-Neptunes
Period_MN= [2,300] # days
Radius_MN= [2.0,4.0] # earth radii
```

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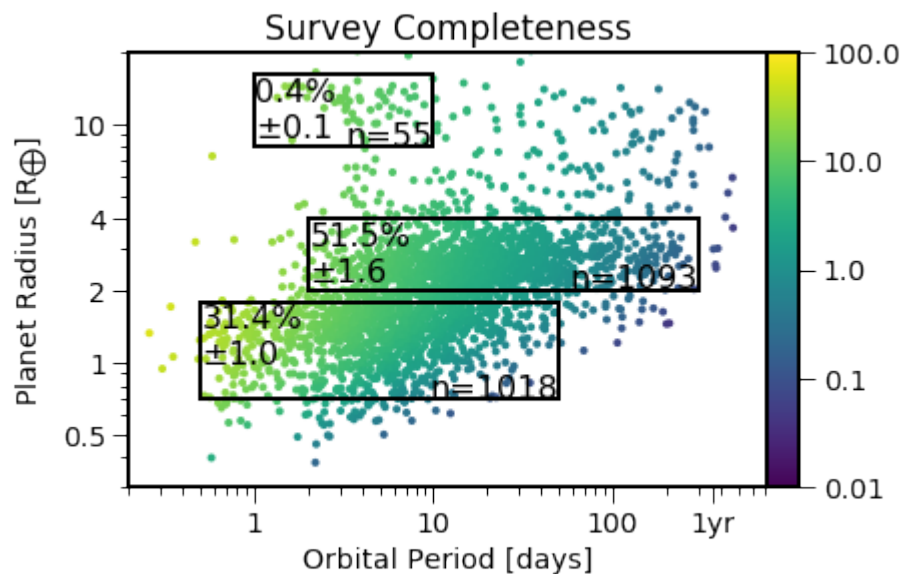
(continued from previous page)

```
epos.set_bins(xbins=[Period_HJ, Period_MN, Period_SE],
              ybins=[Radius_HJ, Radius_MN, Radius_SE])
```

Calculate the occurrence rates and visualize them

```
[5]: EPOS.occurrence.binned(epos)
EPOS.plot.occurrence.colored(epos, Bins=True, NB=True)
```

```
Observed Planets
x: [1,10], y: [8,16], n=55, comp=0.12, occ=0.0043
x: [2,300], y: [2,4], n=1093, comp=0.039, occ=0.52
x: [0.5,50], y: [0.7,1.8], n=1018, comp=0.072, occ=0.31
```



Looks like there are many more super-earths and mini-Neptunes than Hot Juiters!

Now let's calculate occurrence rates on the SAG13 grid

```
[6]: epos.set_bins(xgrid=np.geomspace(10,640,7),
                  ygrid=np.geomspace(0.67,17,9), Grid=True)
EPOS.occurrence.all(epos)
```

Interpolating planet occurrence

```
Observed Planets
x: [10,20], y: [0.67,1], n=16, comp=0.0072, occ=0.022
x: [20,40], y: [0.67,1], n=10, comp=0.0023, occ=0.046
x: [40,80], y: [0.67,1], n=0, comp=nans, occ=0
x: [80,160], y: [0.67,1], n=0, comp=nans, occ=0
x: [160,320], y: [0.67,1], n=0, comp=nans, occ=0
x: [320,640], y: [0.67,1], n=0, comp=nans, occ=0
x: [10,20], y: [1,1.5], n=99, comp=0.021, occ=0.043
x: [20,40], y: [1,1.5], n=30, comp=0.011, occ=0.026
x: [40,80], y: [1,1.5], n=9, comp=0.005, occ=0.019
x: [80,160], y: [1,1.5], n=3, comp=0.001, occ=0.025
```

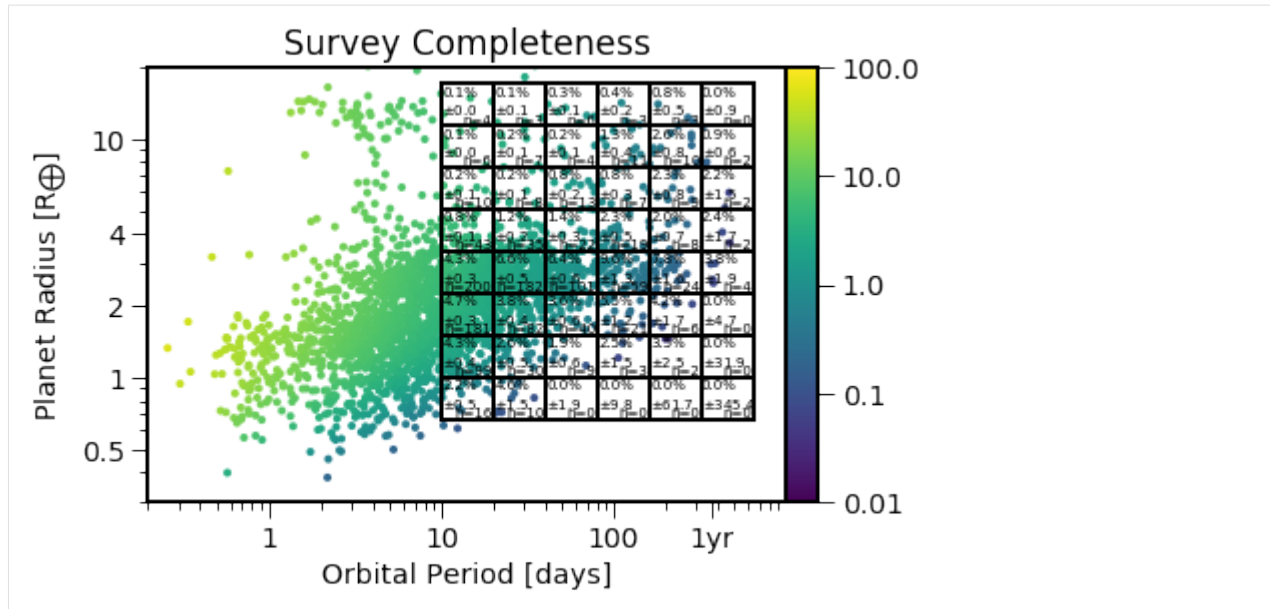
(continues on next page)

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```
x: [160,320], y: [1,1.5], n=2, comp=0.00047, occ=0.035
x: [320,640], y: [1,1.5], n=0, comp=nan, occ=0
x: [10,20], y: [1.5,2.3], n=181, comp=0.033, occ=0.047
x: [20,40], y: [1.5,2.3], n=82, comp=0.018, occ=0.038
x: [40,80], y: [1.5,2.3], n=40, comp=0.01, occ=0.036
x: [80,160], y: [1.5,2.3], n=21, comp=0.0036, occ=0.055
x: [160,320], y: [1.5,2.3], n=6, comp=0.0013, occ=0.042
x: [320,640], y: [1.5,2.3], n=0, comp=nan, occ=0
x: [10,20], y: [2.3,3.4], n=200, comp=0.039, occ=0.043
x: [20,40], y: [2.3,3.4], n=182, comp=0.023, occ=0.066
x: [40,80], y: [2.3,3.4], n=101, comp=0.013, occ=0.064
x: [80,160], y: [2.3,3.4], n=59, comp=0.0055, occ=0.096
x: [160,320], y: [2.3,3.4], n=24, comp=0.0026, occ=0.078
x: [320,640], y: [2.3,3.4], n=4, comp=0.00088, occ=0.038
x: [10,20], y: [3.4,5.1], n=43, comp=0.044, occ=0.0082
x: [20,40], y: [3.4,5.1], n=35, comp=0.024, occ=0.012
x: [40,80], y: [3.4,5.1], n=22, comp=0.014, occ=0.014
x: [80,160], y: [3.4,5.1], n=19, comp=0.0069, occ=0.023
x: [160,320], y: [3.4,5.1], n=8, comp=0.0034, occ=0.02
x: [320,640], y: [3.4,5.1], n=2, comp=0.00071, occ=0.024
x: [10,20], y: [5.1,7.6], n=10, comp=0.047, occ=0.0018
x: [20,40], y: [5.1,7.6], n=8, comp=0.027, occ=0.0024
x: [40,80], y: [5.1,7.6], n=13, comp=0.014, occ=0.0077
x: [80,160], y: [5.1,7.6], n=7, comp=0.0078, occ=0.0076
x: [160,320], y: [5.1,7.6], n=9, comp=0.0033, occ=0.023
x: [320,640], y: [5.1,7.6], n=2, comp=0.00075, occ=0.022
x: [10,20], y: [7.6,11], n=6, comp=0.049, occ=0.001
x: [20,40], y: [7.6,11], n=7, comp=0.028, occ=0.0021
x: [40,80], y: [7.6,11], n=4, comp=0.016, occ=0.0022
x: [80,160], y: [7.6,11], n=11, comp=0.007, occ=0.013
x: [160,320], y: [7.6,11], n=10, comp=0.0034, occ=0.026
x: [320,640], y: [7.6,11], n=2, comp=0.0019, occ=0.0088
x: [10,20], y: [11,17], n=4, comp=0.045, occ=0.00074
x: [20,40], y: [11,17], n=3, comp=0.028, occ=0.00089
x: [40,80], y: [11,17], n=6, comp=0.016, occ=0.0032
x: [80,160], y: [11,17], n=3, comp=0.0068, occ=0.0036
x: [160,320], y: [11,17], n=3, comp=0.0032, occ=0.0082
x: [320,640], y: [11,17], n=0, comp=nan, occ=0
```

```
/Users/mulders/anaconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:3257:
↳RuntimeWarning: Mean of empty slice.
    out=out, **kwargs)
/Users/mulders/anaconda3/lib/python3.7/site-packages/numpy/core/_methods.py:161:
↳RuntimeWarning: invalid value encountered in double_scalars
    ret = ret.dtype.type(ret / rcount)
```

```
[7]: epos.plotpars['textsize']= 7
      epos.xtrim[1]= 1000
      EPOS.plot.occurrence.colored(epos, Bins=True, NB=True)
```



Save the binned rates to a file: `json/occurrence_rate_inverse/occurrence.inverse.json`

```
[8]: EPOS.save_occurrence(epos)
```

3.6 Parametric Mode

Estimate the intrinsic distribution of planets by fitting a double broken power-law in period and radius to the Kepler data

```
[1]: import EPOS
import numpy as np
import matplotlib.pyplot as plt
```

```
initialize the EPOS class
```

```
[2]: epos= EPOS.epos (name='example_1')
```

```
|~| epos 3.0.0.dev2 |~|
```

```
Using random seed 1099836816
```

Read in the kepler dr25 exoplanets and survey efficiency packaged with EPOS

```
[3]: obs, survey= EPOS.kepler.dr25(Huber=True, Vetting=True, score=0.9)
```

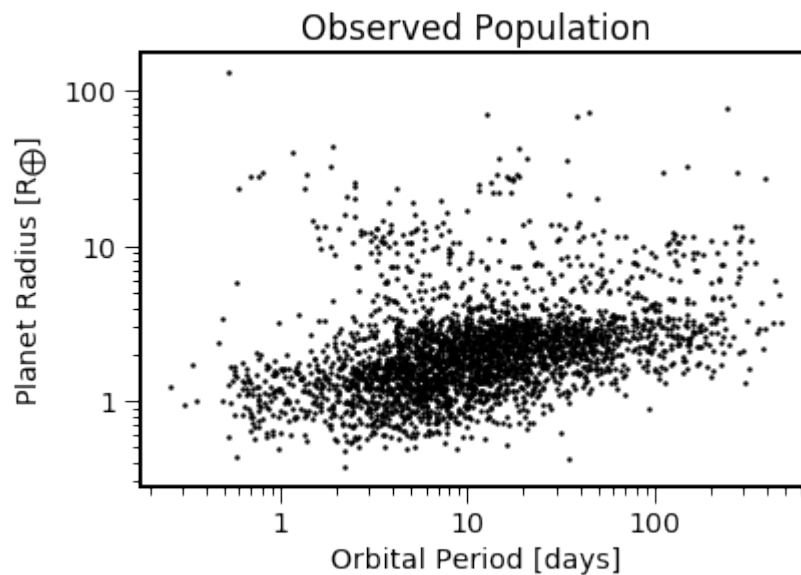
```
Loading planets from temp/q1_q17_dr25_koi.npz
6853/7995 dwarfs
3525 candidates, 3328 false positives
3040+1 with score > 0.90
```

Load and display the observed planet candidates

```
[4]: epos.set_observation(**obs)
      EPOS.plot_survey.observed(epos, NB=True, PlotBox=False)
```

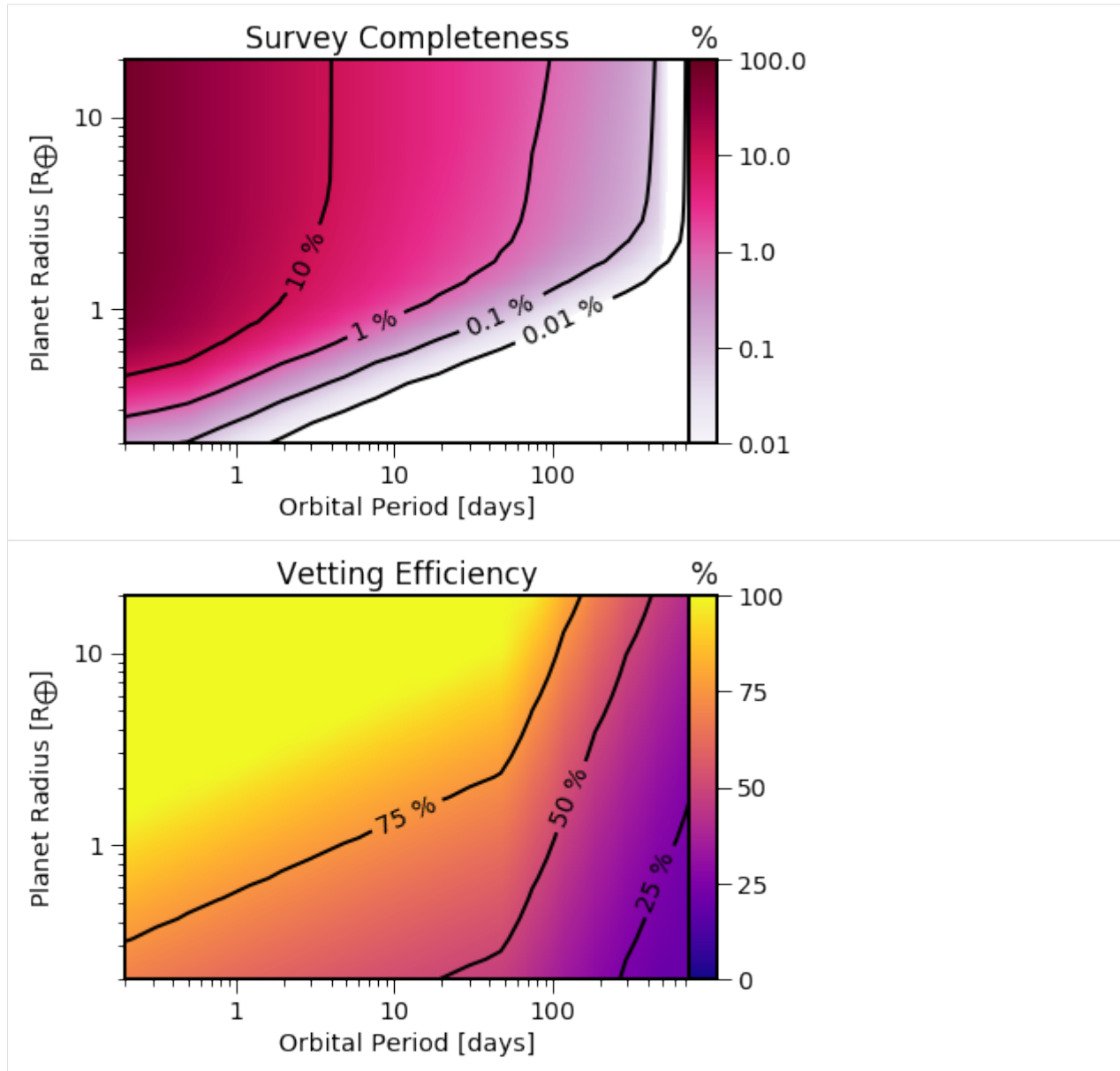
```
Observations:
  159238 stars
  3041 planets

  1840 singles, 487 multis
  - single: 1840
  - double: 324
  - triple: 113
  - quad: 38
  - quint: 10
  - sext: 2
```



Load and display the survey detection efficiency

```
[5]: epos.set_survey(**survey)
      EPOS.plot_survey.completeness(epos, NB=True, PlotBox=False)
      EPOS.plot_survey.vetting(epos, PlotBox=False, NB=True)
```



Define the function that describes the intrinsic planet population. Here we use a double broken power-law from `EPOS.fitfunctions`.

```
[6]: epos.set_parametric(EPOS.fitfunctions.brokenpowerlaw2D)
```

`brokenpowerlaw2D` takes 8 parameters. The two dependent parameters are the period and radius. There are 6 free parameters (`xp`, `p1`, `p2`, `yp`, `p3`, `p4`) and a normalization parameter. Let's define them:

The normalization parameter, labeled `pps`, defines the integrated planet occurrence rate over the radius and period range (defined later on). Let's use two planets per star as a starting guess, and exclude negative numbers with the `min` keyword.

```
[7]: epos.fitpars.add('pps', 2.0, min=0, isnorm=True)
```

Initialize the 6 free parameters that define the shape of the 2D period-radius distribution, and their allowed ranges (`min`, `max`).

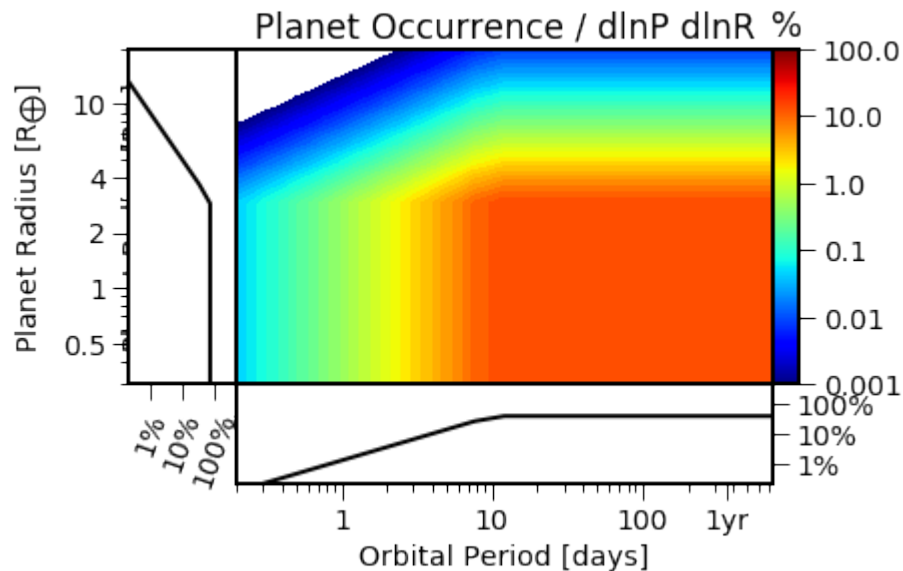
```
[8]: epos.fitpars.add('P break', 10., min=2, max=50, is2D=True)
      epos.fitpars.add('a_P', 1.5, min=0, is2D=True)
      epos.fitpars.add('b_P', 0.0, dx=0.1, is2D=True)
      epos.fitpars.add('R break', 3.0, min=1.0, max=5, is2D=True)
      epos.fitpars.add('a_R', 0.0, dx=0.1, is2D=True)
      epos.fitpars.add('b_R', -4., fixed=True, is2D=True)
```

define the simulated range (trim) and the range compared to observations (zoom)

```
[9]: epos.set_ranges(xtrim=[0,730],ytrim=[0.3,20.],xzoom=[2,400],yzoom=[1,6], Occ=True)
```

Show the initial distribution

```
[10]: EPOS.plot.parametric.panels(epos, NB=True)
```



Generate an observable planet population with the initial guess and compare it to Kepler

```
[11]: EPOS.run.once(epos)
```

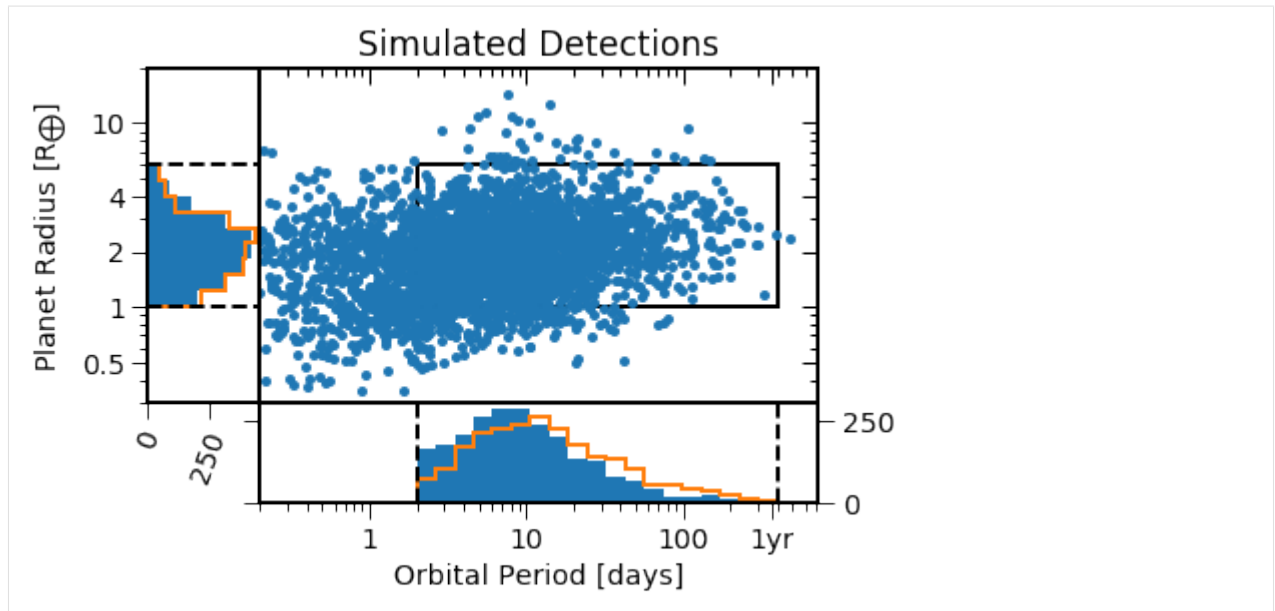
```
Preparing EPOS run...
  6 fit parameters

Starting the first MC run

Goodness-of-fit
  logp= -54.1
  - p(n=2398)=0.44
  - p(x)=3.1e-23
  - p(y)=0.24
  observation comparison in 0.003 sec
Finished one MC in 0.063 sec
```

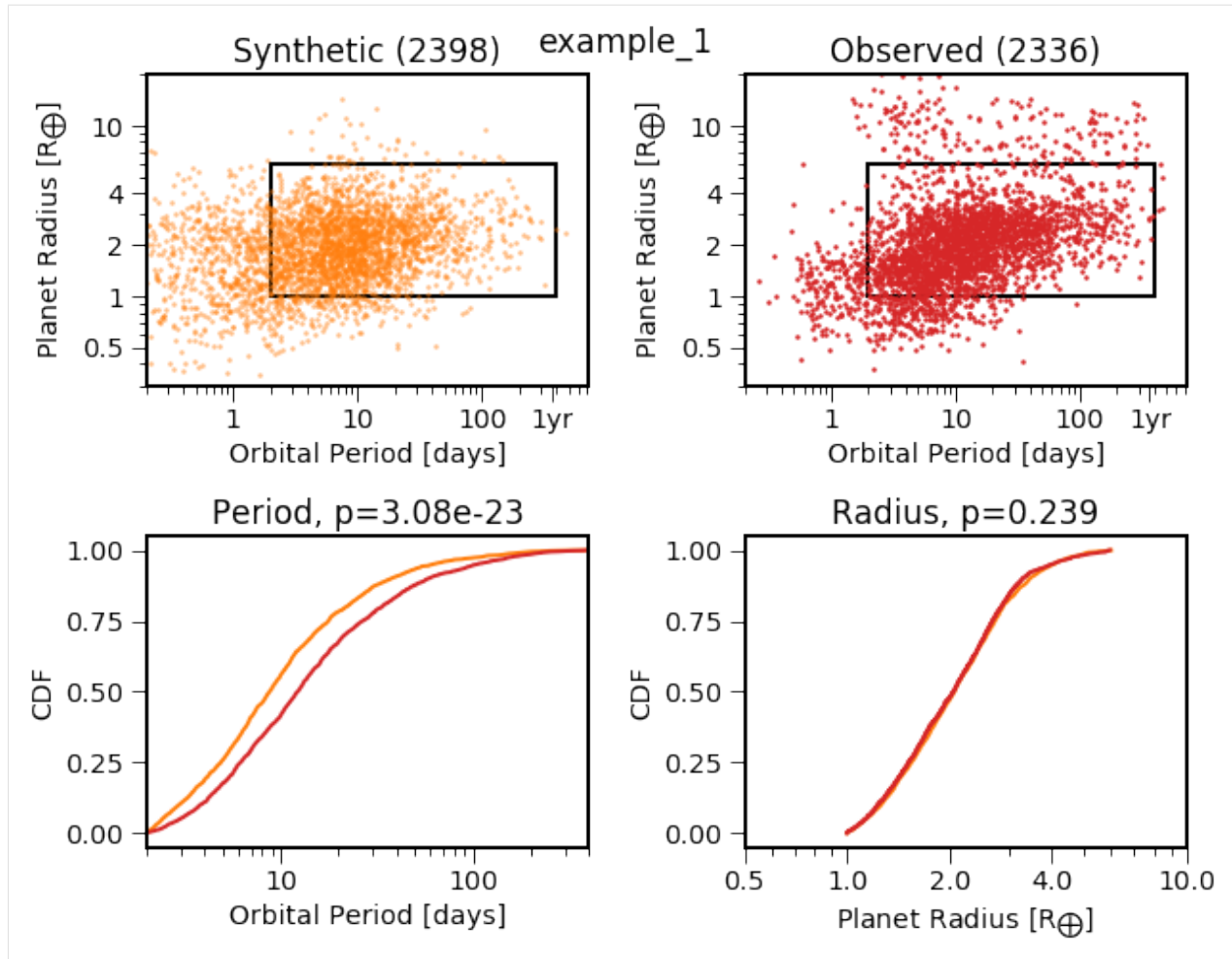
Show the simulated detections

```
[12]: EPOS.plot.periodradius.panels(epos, NB=True)
```



Show the cumulative distributions used for the summary statistics

```
[13]: EPOS.plot.periodradius.cdf(epos, NB=True)
```



Looks like the simulated period distribution is a bit different from what is observed. Let's minimize the distance between the distributions using emcee. (Note the counter doesn't work yet)

```
[14]: EPOS.run.mcmc(epos, nMC=1000, nwalkers=100, nburn=200, threads=8, Saved=True)
```

```
Loading saved status from chain/example_1/100x1000x6.npz
```

```
NOTE: Random seed changed: 2553310461 to 1099836816
```

```
MC-ing the 30 samples to plot
```

```
Best-fit values
```

```
pps= 3.92 +1.18 -0.959
P break= 13 +4.11 -3.24
a_P= 1.57 +0.444 -0.213
b_P= 0.184 +0.129 -0.144
R break= 2.93 +0.159 -0.184
a_R= -0.29 +0.312 -0.194
```

```
Starting the best-fit MC run
```

```
Goodness-of-fit
```

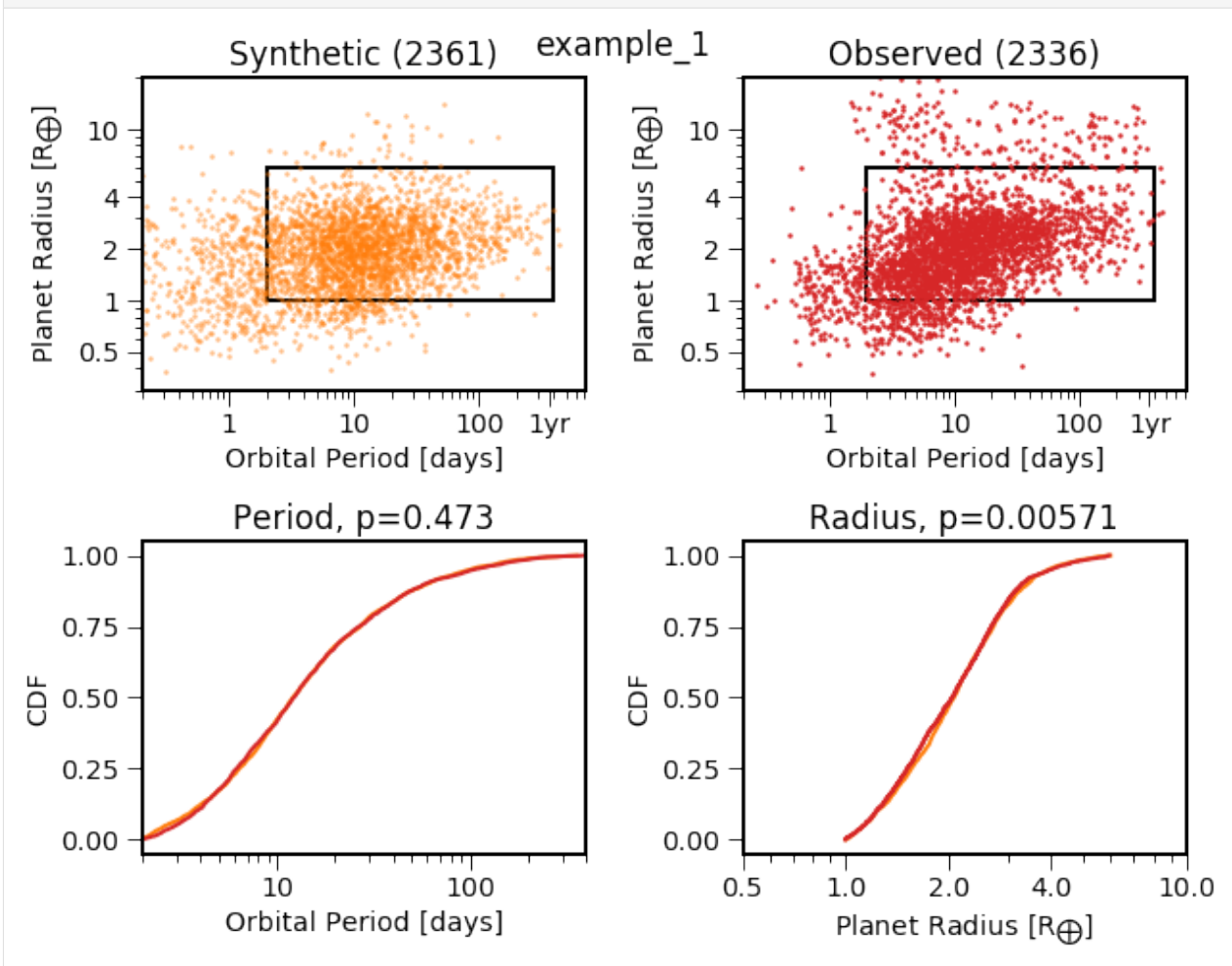
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```
logp= -6.0
- p(n=2361)=0.87
- p(x)=0.47
- p(y)=0.0057

Akaike/Bayesian Information Criterion
- k=6, n=2336
- BIC= 58.6
- AIC= 24.1, AICc= 0.9
observation comparison in 0.004 sec
```

```
[15]: EPOS.plot.periodradius.cdf(epos, NB=True)
```

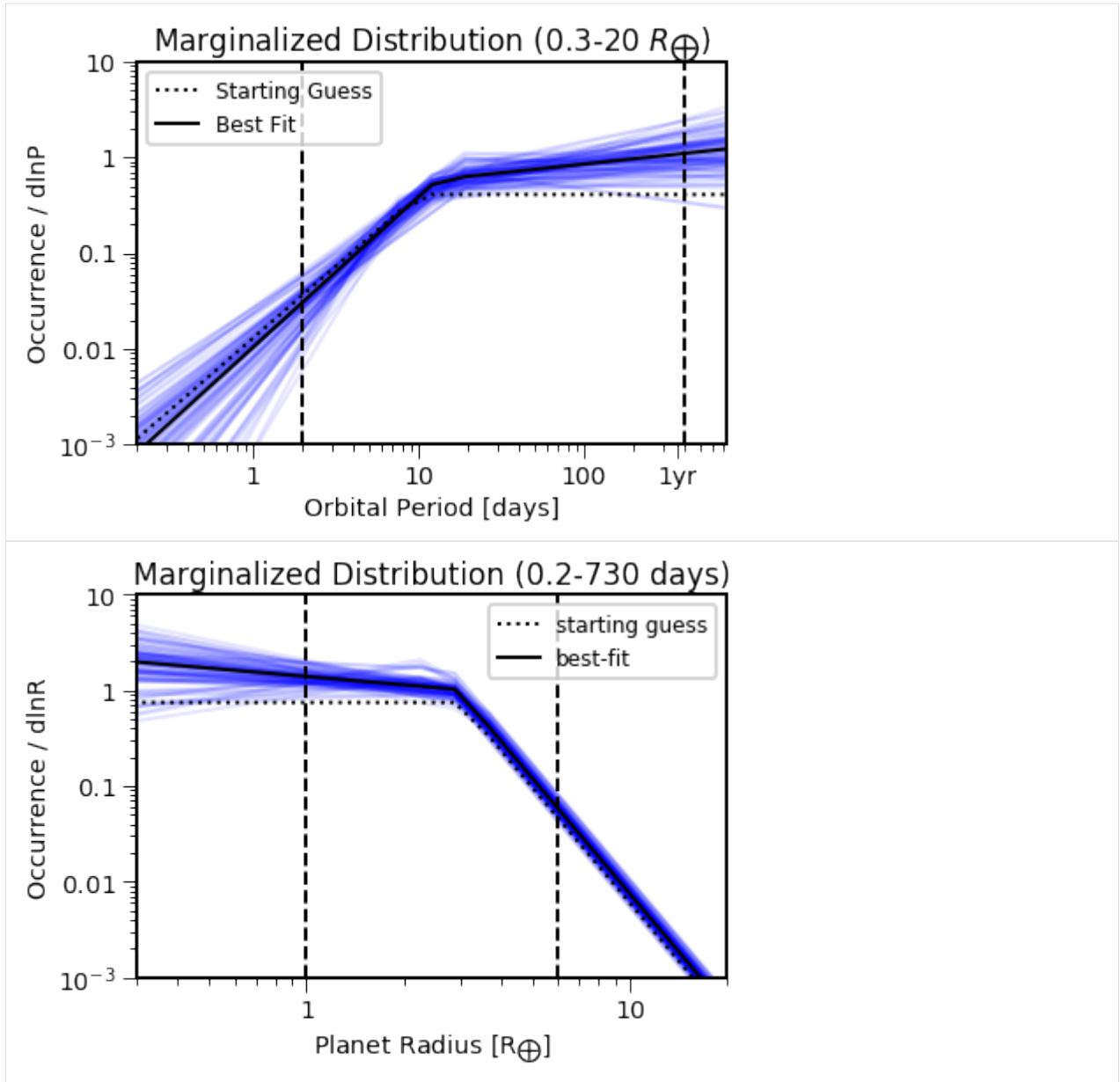


That looks better!

```
[16]: #EPOS.plot.mcmc.corners(epos, NB=True)
#EPOS.plot.mcmc.chain(epos, NB=True)
```

Let's look at the posterior distributions

```
[17]: EPOS.plot.parametric.oneD_x(epos, MCMC=True, NB=True)
EPOS.plot.parametric.oneD_y(epos, MCMC=True, NB=True)
```



And compare them to the planet occurrence rates

```
[18]: EPOS.occurrence.all(epos)
      EPOS.plot.parametric.oneD_x(epos, MCMC=True, NB=True, Occ=True)
      EPOS.plot.parametric.oneD_y(epos, MCMC=True, NB=True, Occ=True)
```

Interpolating planet occurrence

```
x zoom bins
x: [2,400], y: [0.25,0.32], n=0, comp=nan, occ=0
x: [2,400], y: [0.32,0.41], n=1, comp=0.0011, occ=0.0055
x: [2,400], y: [0.41,0.53], n=8, comp=0.002, occ=0.82
x: [2,400], y: [0.53,0.67], n=42, comp=0.0067, occ=0.11
x: [2,400], y: [0.67,0.86], n=106, comp=0.016, occ=0.11
```

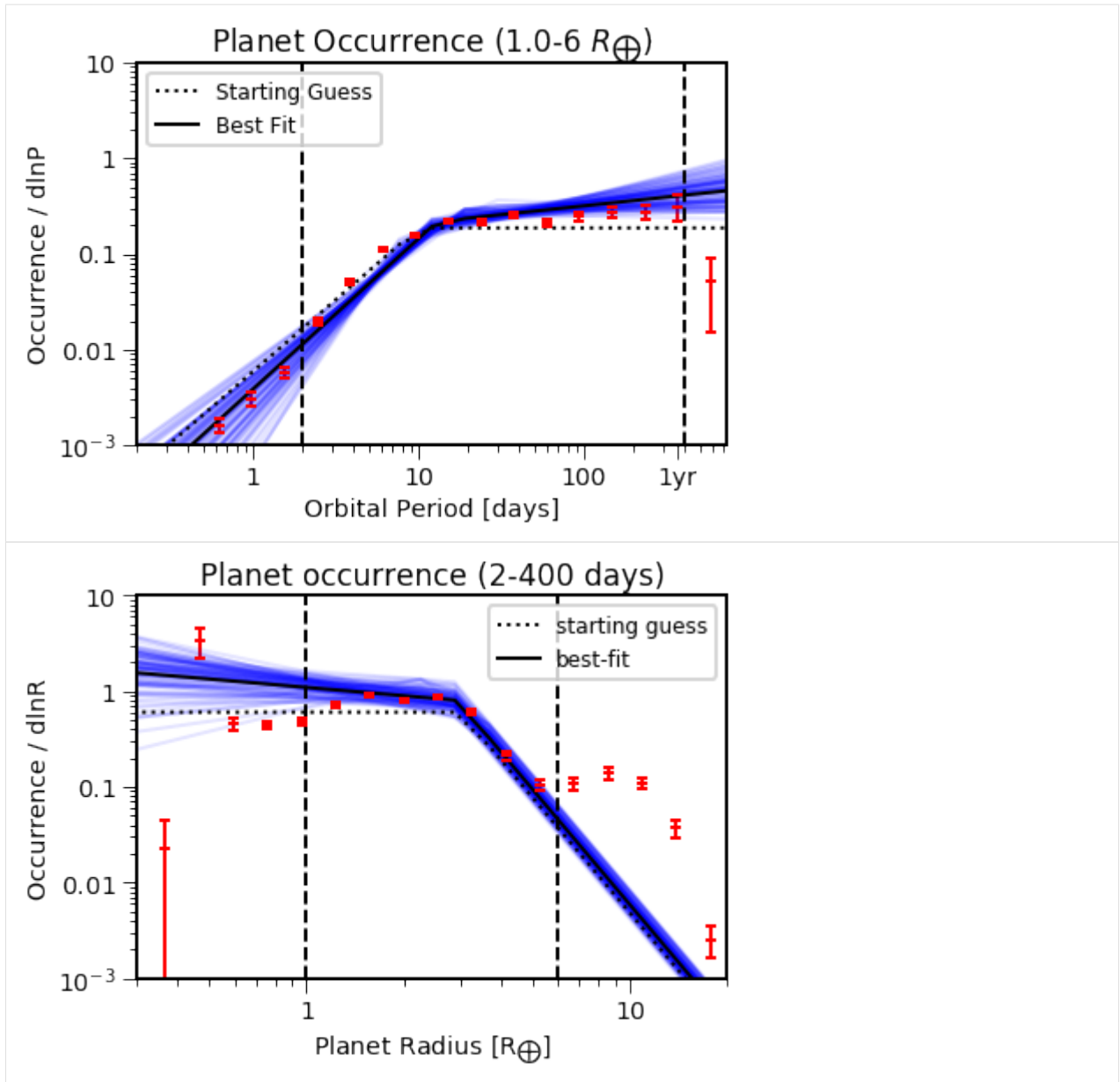
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```
x: [2,400], y: [0.86,1.1], n=184, comp=0.029, occ=0.12
x: [2,400], y: [1.1,1.4], n=346, comp=0.039, occ=0.18
x: [2,400], y: [1.4,1.8], n=475, comp=0.042, occ=0.22
x: [2,400], y: [1.8,2.3], n=466, comp=0.035, occ=0.19
x: [2,400], y: [2.3,2.9], n=520, comp=0.035, occ=0.21
x: [2,400], y: [2.9,3.7], n=290, comp=0.031, occ=0.15
x: [2,400], y: [3.7,4.7], n=104, comp=0.037, occ=0.051
x: [2,400], y: [4.7,6], n=54, comp=0.038, occ=0.025
x: [2,400], y: [6,7.6], n=46, comp=0.041, occ=0.026
x: [2,400], y: [7.6,9.7], n=48, comp=0.034, occ=0.034
x: [2,400], y: [9.7,12], n=51, comp=0.054, occ=0.027
x: [2,400], y: [12,16], n=25, comp=0.061, occ=0.009
x: [2,400], y: [16,20], n=8, comp=0.091, occ=0.00062

y zoom bins
x: [0.2,0.315], y: [1,6], n=1, comp=0.52, occ=1.2e-05
x: [0.315,0.498], y: [1,6], n=4, comp=0.41, occ=6.2e-05
x: [0.498,0.785], y: [1,6], n=32, comp=0.27, occ=0.00075
x: [0.785,1.24], y: [1,6], n=43, comp=0.2, occ=0.0014
x: [1.24,1.95], y: [1,6], n=58, comp=0.14, occ=0.0026
x: [1.95,3.08], y: [1,6], n=135, comp=0.099, occ=0.0088
x: [3.08,4.86], y: [1,6], n=259, comp=0.072, occ=0.024
x: [4.86,7.66], y: [1,6], n=381, comp=0.05, occ=0.051
x: [7.66,12.1], y: [1,6], n=390, comp=0.037, occ=0.072
x: [12.1,19.1], y: [1,6], n=389, comp=0.027, occ=0.1
x: [19.1,30.1], y: [1,6], n=267, comp=0.019, occ=0.098
x: [30.1,47.4], y: [1,6], n=217, comp=0.014, occ=0.12
x: [47.4,74.8], y: [1,6], n=120, comp=0.0093, occ=0.097
x: [74.8,118], y: [1,6], n=85, comp=0.0057, occ=0.11
x: [118,186], y: [1,6], n=58, comp=0.0033, occ=0.12
x: [186,293], y: [1,6], n=32, comp=0.0021, occ=0.12
x: [293,463], y: [1,6], n=11, comp=0.0008, occ=0.14
x: [463,730], y: [1,6], n=2, comp=0.00053, occ=0.024
```

```
/Users/mulders/anaconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:2920:
↳RuntimeWarning: Mean of empty slice.
    out=out, **kwargs)
/Users/mulders/anaconda3/lib/python3.7/site-packages/numpy/core/_methods.py:85:
↳RuntimeWarning: invalid value encountered in double_scalars
    ret = ret.dtype.type(ret / rcount)
```



Now let's extrapolate into the Habitable Zone

```
[19]: epos.set_bins(xbins=[[0.9*365,2.2*365]], ybins=[[0.7,1.5]])
      EPOS.occurrence.all(epos)
```

Interpolating planet occurrence

Observed Planets

x: [328,803], y: [0.7,1.5], n=0, comp=nan, occ=0

x zoom bins

x: [2,400], y: [0.25,0.32], n=0, comp=nan, occ=0

x: [2,400], y: [0.32,0.41], n=1, comp=0.0011, occ=0.0055

x: [2,400], y: [0.41,0.53], n=8, comp=0.002, occ=0.82

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```
x: [2,400], y: [0.53,0.67], n=42, comp=0.0067, occ=0.11
x: [2,400], y: [0.67,0.86], n=106, comp=0.016, occ=0.11
x: [2,400], y: [0.86,1.1], n=184, comp=0.029, occ=0.12
x: [2,400], y: [1.1,1.4], n=346, comp=0.039, occ=0.18
x: [2,400], y: [1.4,1.8], n=475, comp=0.042, occ=0.22
x: [2,400], y: [1.8,2.3], n=466, comp=0.035, occ=0.19
x: [2,400], y: [2.3,2.9], n=520, comp=0.035, occ=0.21
x: [2,400], y: [2.9,3.7], n=290, comp=0.031, occ=0.15
x: [2,400], y: [3.7,4.7], n=104, comp=0.037, occ=0.051
x: [2,400], y: [4.7,6], n=54, comp=0.038, occ=0.025
x: [2,400], y: [6,7.6], n=46, comp=0.041, occ=0.026
x: [2,400], y: [7.6,9.7], n=48, comp=0.034, occ=0.034
x: [2,400], y: [9.7,12], n=51, comp=0.054, occ=0.027
x: [2,400], y: [12,16], n=25, comp=0.061, occ=0.009
x: [2,400], y: [16,20], n=8, comp=0.091, occ=0.00062
```

y zoom bins

```
x: [0.2,0.315], y: [1,6], n=1, comp=0.52, occ=1.2e-05
x: [0.315,0.498], y: [1,6], n=4, comp=0.41, occ=6.2e-05
x: [0.498,0.785], y: [1,6], n=32, comp=0.27, occ=0.00075
x: [0.785,1.24], y: [1,6], n=43, comp=0.2, occ=0.0014
x: [1.24,1.95], y: [1,6], n=58, comp=0.14, occ=0.0026
x: [1.95,3.08], y: [1,6], n=135, comp=0.099, occ=0.0088
x: [3.08,4.86], y: [1,6], n=259, comp=0.072, occ=0.024
x: [4.86,7.66], y: [1,6], n=381, comp=0.05, occ=0.051
x: [7.66,12.1], y: [1,6], n=390, comp=0.037, occ=0.072
x: [12.1,19.1], y: [1,6], n=389, comp=0.027, occ=0.1
x: [19.1,30.1], y: [1,6], n=267, comp=0.019, occ=0.098
x: [30.1,47.4], y: [1,6], n=217, comp=0.014, occ=0.12
x: [47.4,74.8], y: [1,6], n=120, comp=0.0093, occ=0.097
x: [74.8,118], y: [1,6], n=85, comp=0.0057, occ=0.11
x: [118,186], y: [1,6], n=58, comp=0.0033, occ=0.12
x: [186,293], y: [1,6], n=32, comp=0.0021, occ=0.12
x: [293,463], y: [1,6], n=11, comp=0.0008, occ=0.14
x: [463,730], y: [1,6], n=2, comp=0.00053, occ=0.024
```

posterior per bin

```
x: [328,803], y: [0.7,1.5], area=0.68, eta_0=0.1
gamma= 40.2% +17.4% -13.4%
eta= 27.4% +11.8% -9.1%
```

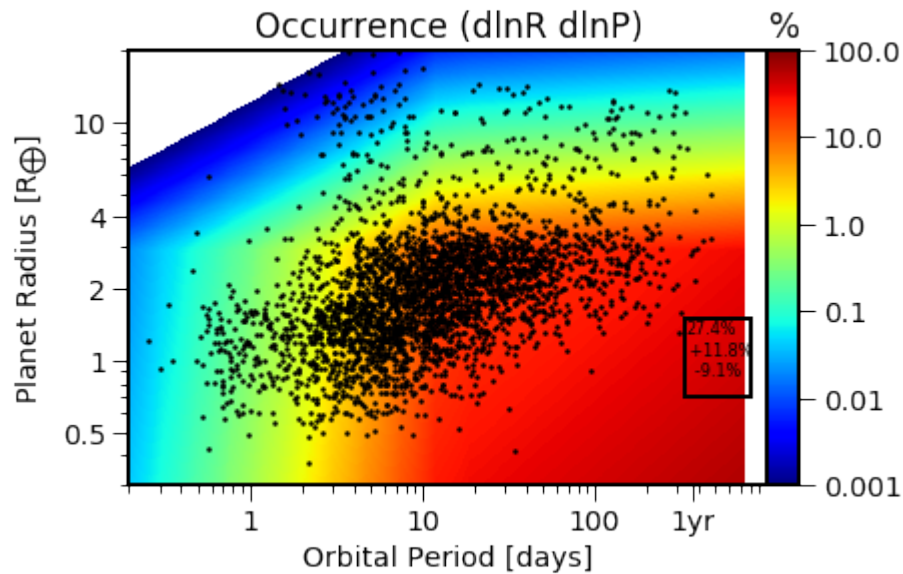
Binned occurrence rate metrics

```
x: (n=12, k=6)
  chi^2= 147.3, reduced= 24.6
  bic= 45.0
  aic= 71.9, AICc= 1208.1
y: (n=7, k=6)
  chi^2= 79.3, reduced= 79.3
  bic= 28.7
  aic= 42.6, AICc= inf
```

```
/Users/mulders/EPOS/EPOS/analytics.py:67: RuntimeWarning: divide by zero encountered_
↪in double_scalars
  cfactor= (2.* k_free**2. + 2.*k_free) / (n_data- k_free - 1.)
```

And visualize the distribution

```
[20]: epos.plotpars['textsize']= 8 # Shrink text to fit in the box
      epos.xtrim[1]= 1000 # Adjust plot axes
      EPOS.plot.occurrence.integrated(epos, MCMC=True, Planets=True, NB=True)
```



```
[ ]:
```

3.7 Multi-planet Mode

Estimate the intrinsic distribution of planetary systems by fitting a population of multi-planet systems to Kepler data

```
[1]: import EPOS
      import numpy as np
      import matplotlib.pyplot as plt
```

initialize the EPOS class

```
[2]: epos= EPOS.epos(name='example_2')
```

```
|~| epos 3.0.0.dev2 |~|
```

Using random seed 493439428

Read in the kepler dr25 exoplanets and survey efficiency packaged with EPOS

```
[3]: obs, survey= EPOS.kepler.dr25(Huber=True, Vetting=True, score=0.9)
      epos.set_observation(**obs)
      epos.set_survey(**survey)
```

```
Loading planets from temp/q1_q17_dr25_koi.npz
6853/7995 dwarfs
```

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```
3525 candidates, 3328 false positives
3040+1 with score > 0.90

Observations:
159238 stars
3041 planets

1840 singles, 487 multis
- single: 1840
- double: 324
- triple: 113
- quad: 38
- quint: 10
- sext: 2
```

Define the function that describes the intrinsic planetary system population. Here we use a double broken power-law from EPOS.fitfunctions to define the location and size of the innermost planet in each system.

```
[4]: epos.set_parametric(EPOS.fitfunctions.brokenpowerlaw2D)
```

brokenpowerlaw2D takes 8 parameters. The two dependent parameters are the period and radius. There are 6 free parameters (xp, p1, p2, yp, p3, p4) and a normalization parameter. Let's define them:

The normalization parameter, labeled pps, defines the fraction of stars with planetary systems. Let's assign a planetary system to 40% of stars, and exclude negative numbers with the min keyword.

```
[5]: epos.fitpars.add('pps', 0.4, min=0, isnorm=True)
```

Initialize the 6 parameters that define the distribution of the innermost planets, fixing the radius distribution.

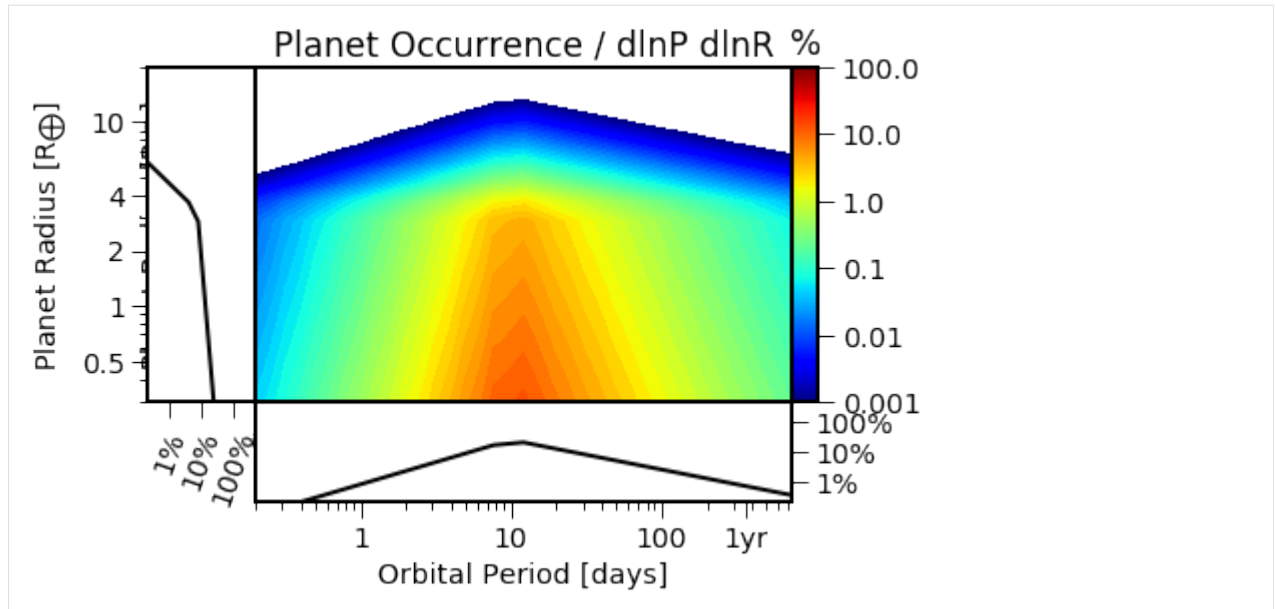
```
[6]: epos.fitpars.add('P break', 10., min=2, max=50, is2D=True)
epos.fitpars.add('a_P', 1.5, min=0, is2D=True)
epos.fitpars.add('b_P', -1, max=1, dx=0.1, is2D=True)
epos.fitpars.add('R break', 3.3, fixed=True, is2D=True)
epos.fitpars.add('a_R', -0.5, fixed=True, is2D=True)
epos.fitpars.add('b_R', -6., fixed=True, is2D=True)
```

define the simulated range (trim) and the range compared to observations (zoom)

```
[7]: epos.set_ranges(xtrim=[0, 730], ytrim=[0.3, 20.], xzoom=[2, 400], yzoom=[1, 6], Occ=True)
```

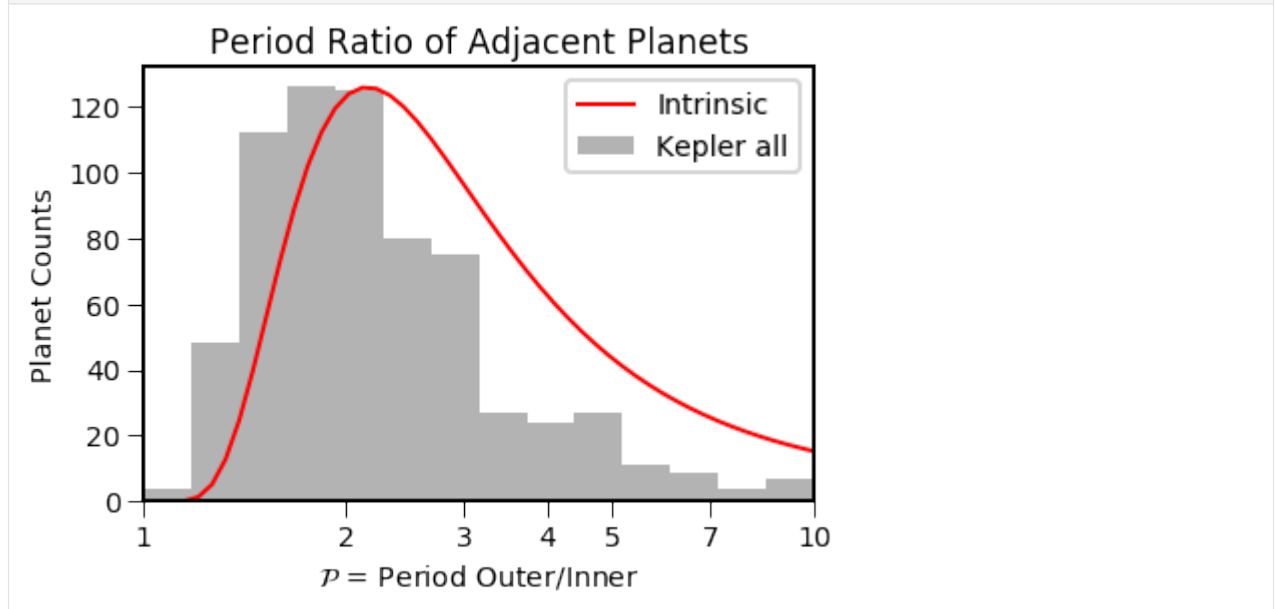
Show the inner planet distribution

```
[8]: EPOS.plot.parametric.panels(epos, NB=True)
```



Define the locations of additional planets in the system. Here, let's use 10 planets per system, with the spacing drawn from a dimensionless distribution

```
[9]: epos.set_multi(spacing='dimensionless')
      epos.fitpars.add('npl', 10, fixed=True) # planets per system
      epos.fitpars.add('log D', -0.3)
      epos.fitpars.add('sigma', 0.2, min=0)
      EPOS.plot.multi.periodratio(epos, Input=True, MC=False, NB=True)
```



Define the mutual inclinations, drawn from Rayleigh distribution with mode 2 degrees

```
[10]: epos.fitpars.add('inc', 2.0) # mode of mutual_
      ↪ inclinations
```

Fraction of system with high mutual inclunations to fit the Kepler dichotomy

```
[11]: epos.fitpars.add('f_iso', 0.4) # Fraction of isotropic_
      ↪systems
```

Add a dispersion to the radii of planets in each system

```
[12]: epos.fitpars.add('dR', 0.01, fixed=True)
```

Generate an observable planet population with the initial guess and compare it to Kepler

```
[13]: EPOS.run.once(epos)
```

```
Preparing EPOS run...
  6 fit parameters
  Set f_cor to default 0.5

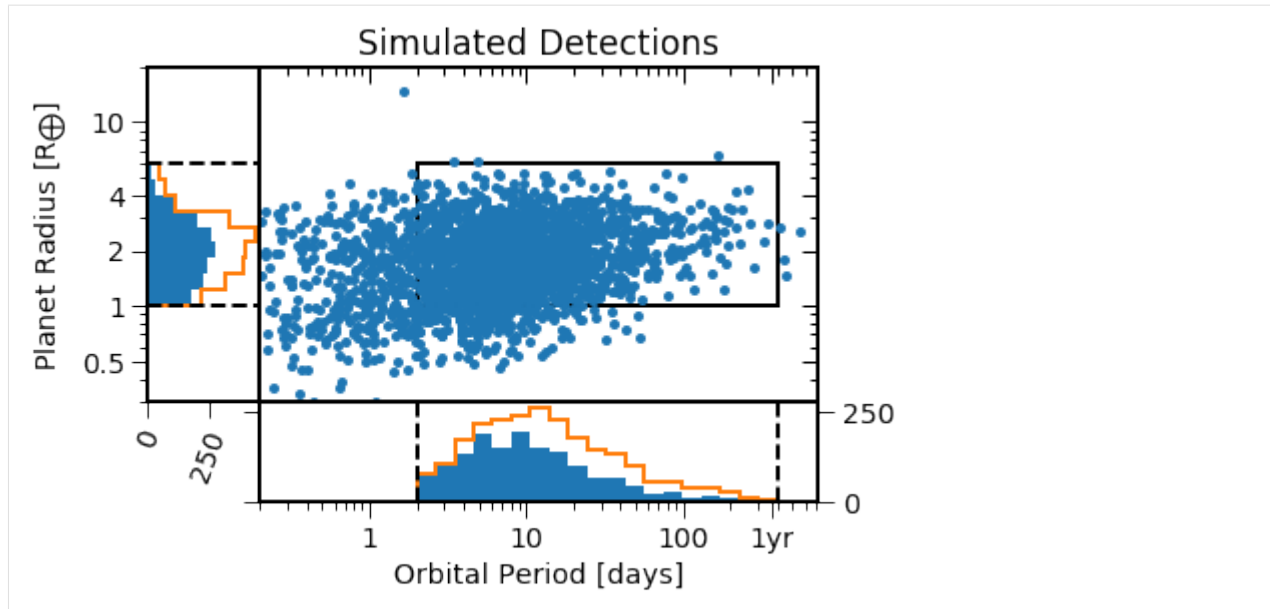
Starting the first MC run
  63695/356370 systems
  Average mutual inc=2.4 degrees

  356370 planets, 9647 transit their star
  - single: 4632
  - double: 1082
  - triple: 456
  - quad: 217
  - quint: 81
  - sext: 24
  - sept: 6
  - oct: 3
  9647 transiting planets, 2145 detectable
  - single: 1263
  - double: 226
  - triple: 87
  - quad: 29
  - quint: 7
  - sext: 3

Goodness-of-fit
  logp= -160.4
  - p(n=1548)=1.9e-58
  - p(x)=3.5e-08
  - p(N_k)=0.84
  - p(P ratio)=0.027
  - p(P inner)=0.0014
  observation comparison in 0.044 sec
Finished one MC in 0.475 sec
```

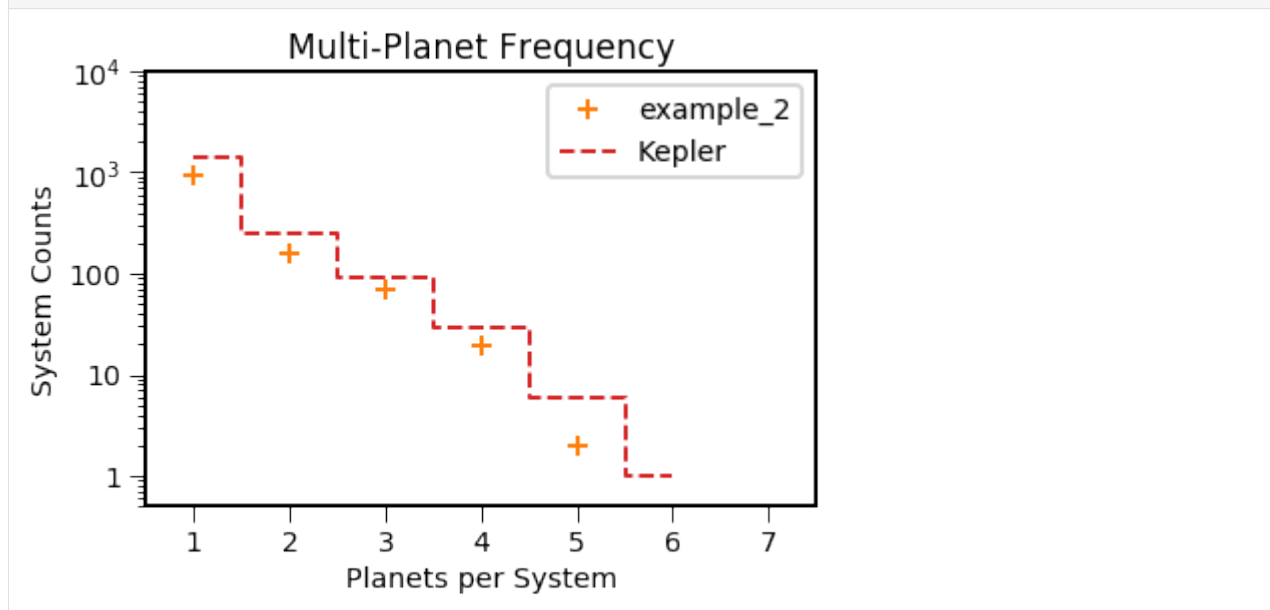
Show the simulated detections

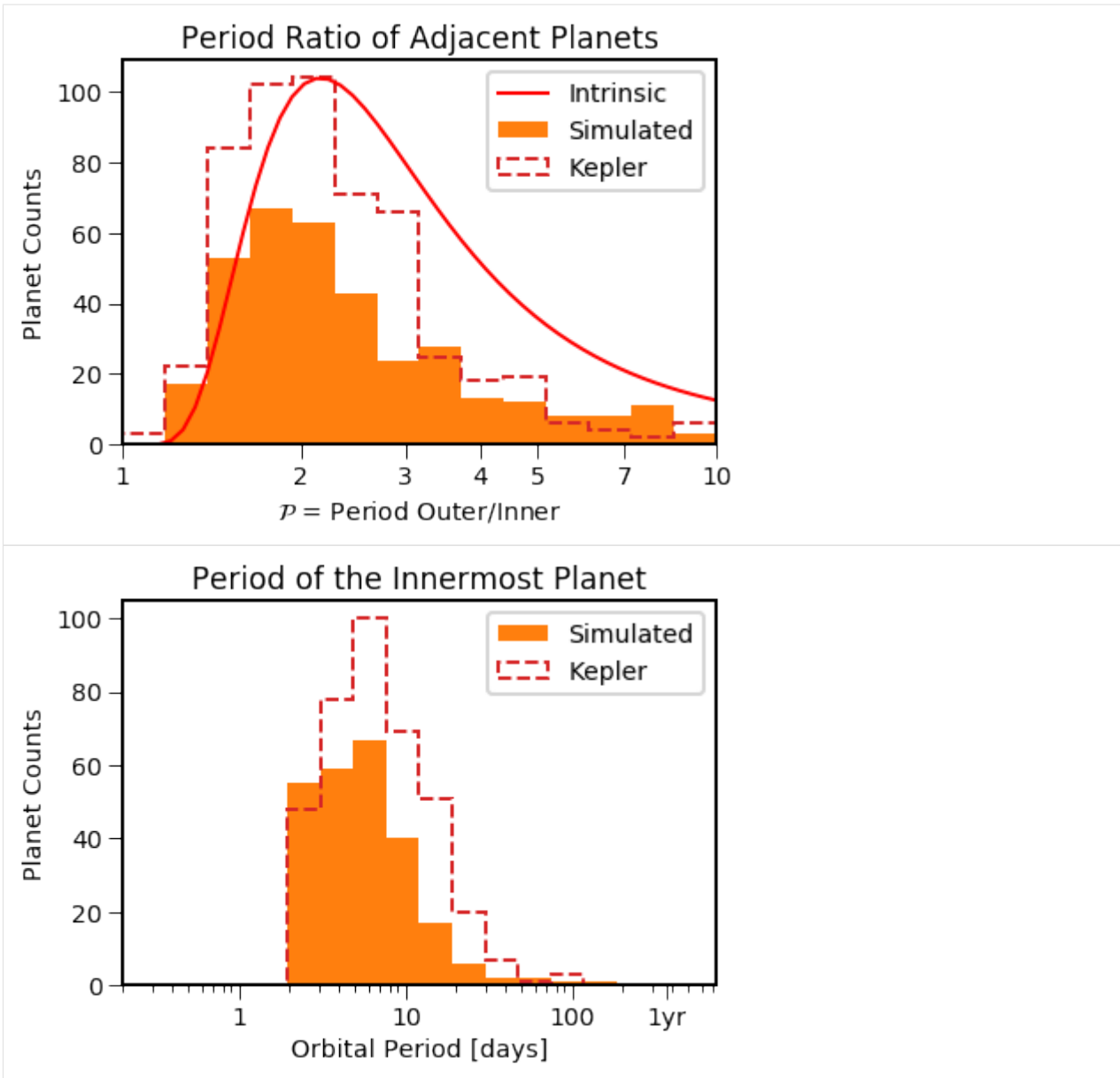
```
[14]: EPOS.plot.periodradius.panels(epos, NB=True)
```



And the detectable planet architectures, compared to the initial distributions

```
[15]: EPOS.plot.multi.multiplicity(epos, MC=True, NB=True)
      EPOS.plot.multi.periodratio(epos, Input=True, MC=True, NB=True)
      EPOS.plot.multi.periodinner(epos, MC=True, NB=True)
```





The simulated distributions are a bit different from what is observed. Let's minimize the distance between the distributions using emcee. (Note the counter doesn't work yet)

```
[16]: EPOS.run.mcmc(epos, nMC=100, nwalkers=20, nburn=20, threads= 8, Saved=True) # ~20 mins
      #EPOS.run.mcmc(epos, nMC=500, nwalkers=50, nburn=200, threads= 8, Saved=True) # ~20
      ↪mins
      #EPOS.run.mcmc(epos, nMC=1000, nwalkers=100, nburn=200, threads=20, Saved=True) # ~5
      ↪hrs
```

Loading saved status from chain/example_2/20x100x8.npz

NOTE: Random seed changed: 3119675631 to 493439428

MC-ing the 30 samples to plot

Mercury analogues < 3.3% +1.2% -1.1%

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```

1 sigma UL 3.9%
2 sigma UL 5.1%
3 sigma UL 12.2%
Venus analogues < 0.9% +0.4% -0.3%
1 sigma UL 1.2%
2 sigma UL 1.6%
3 sigma UL 4.9%

Best-fit values
pps= 0.57 +0.0583 -0.0365
P break= 10.8 +1.87 -1.39
a_P= 1.61 +0.246 -0.191
b_P= -1.3 +0.171 -0.107
log D= -0.345 +0.0311 -0.0343
sigma= 0.187 +0.0225 -0.019
inc= 1.92 +0.684 -0.67
f_iso= 0.418 +0.0635 -0.0459

Starting the best-fit MC run
90776/565953 systems
Average mutual inc=2.3 degrees

565953 planets, 14997 transit their star
- single: 6926
- double: 1572
- triple: 783
- quad: 353
- quint: 133
- sext: 52
- sept: 20
- oct: 5
- nint: 1
14997 transiting planets, 3087 detectable
- single: 1743
- double: 354
- triple: 135
- quad: 34
- quint: 14
- sext: 3
- sept: 1

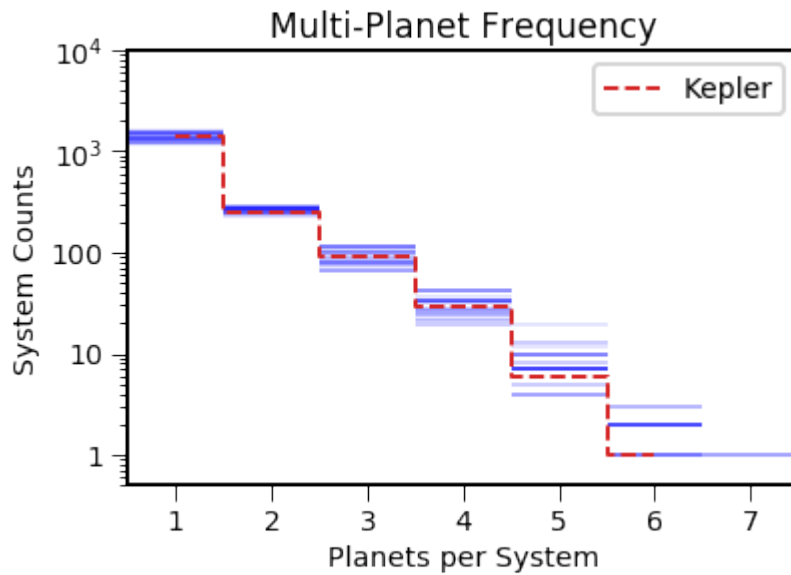
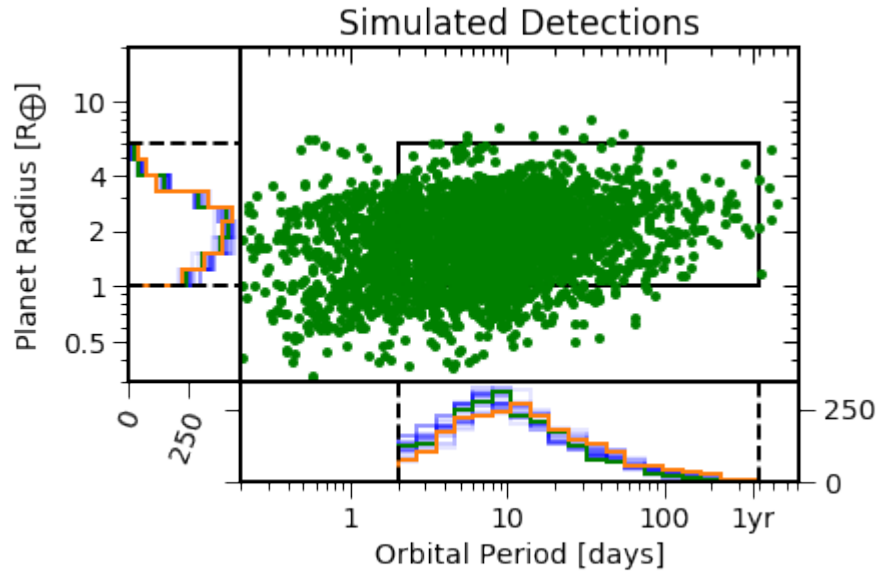
Goodness-of-fit
logp= -13.7
- p(n=2277)=0.47
- p(x)=0.0014
- p(N_k)=0.94
- p(P ratio)=0.11
- p(P inner)=0.016

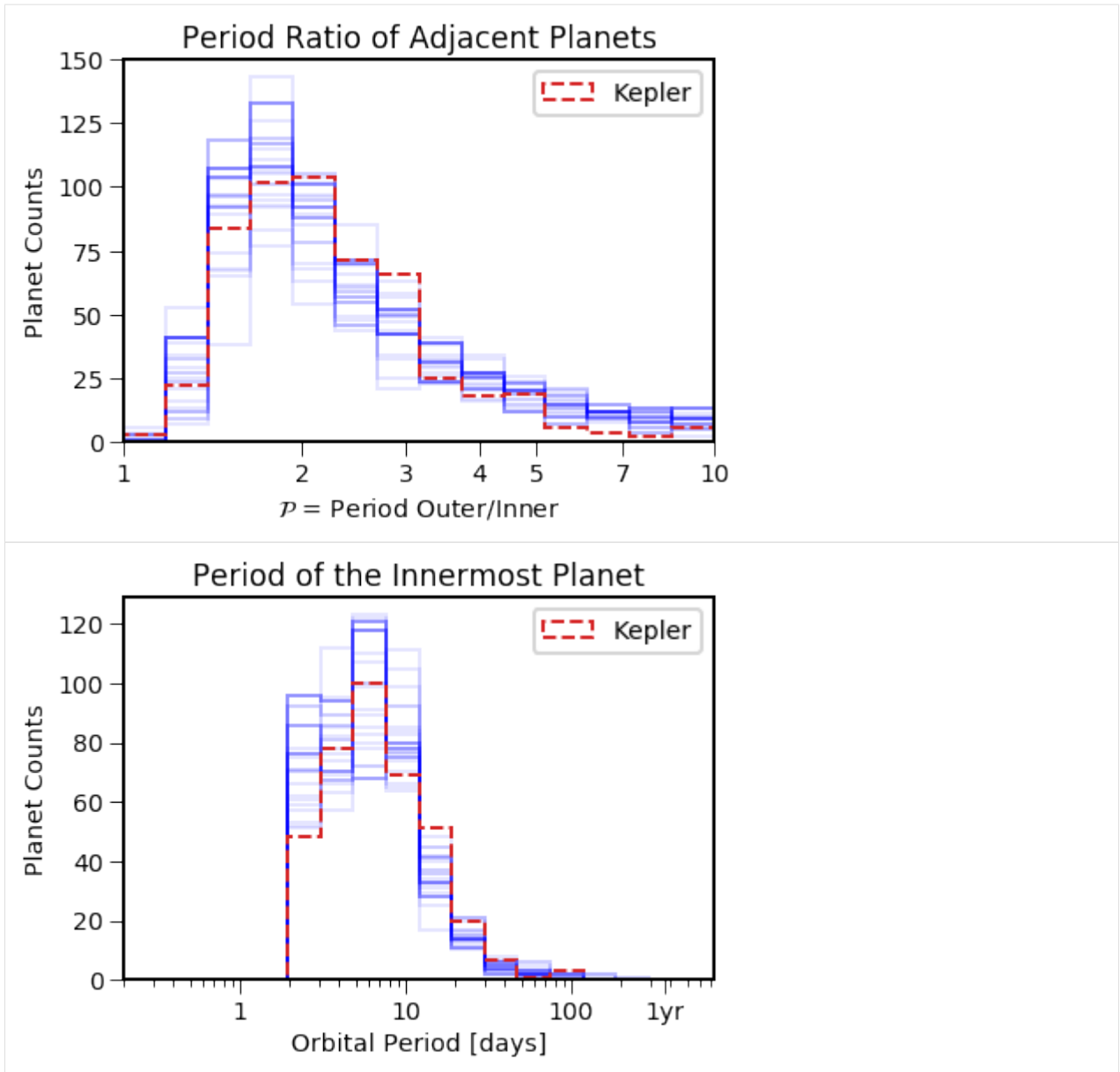
Akaike/Bayesian Information Criterion
- k=8, n=2336
- BIC= 89.4
- AIC= 43.4, AICc= 2.7
observation comparison in 0.083 sec

```

Let's look at the posterior distributions

```
[17]: EPOS.plot.periodradius.panels(epos, MCMC=True, NB=True)
      EPOS.plot.multi.multiplicity(epos, MCMC=True, MC=True, NB=True)
      EPOS.plot.multi.periodratio(epos, MCMC=True, MC=True, NB=True)
      EPOS.plot.multi.periodinner(epos, MCMC=True, MC=True, NB=True)
```





Save the planet populations to a csv file

```
[18]: popdict= dict(all_systems=epos.population,
                    transiting_systems= epos.population['system'],
                    transiting_planets= epos.synthetic_survey)

for key, pop in popdict.items():
    fname= 'csv/'+epos.name+'_'+key
    EPOS.save.to_csv(fname, starID= pop['ID'], Period_days= pop['P'], Radius_earth=
    ↪pop['Y'])
```

```
[ ]:
```

3.8 Radial Velocity

Example script fitting a power-law in period and $M \sin i$ to radial velocity data

First, let's import EPOS

```
[1]: import EPOS
```

Then initialize the EPOS class for use with a radial velocity survey using the RV keyword. We don't want to use the Monte Carlo simulation because of the small sample size ($MC=False$). And we want to fit the intrinsic mass distribution, so we need to convert to $M \sin i$ before fitting the observed planets ($Msini=False$).

```
[2]: epos = EPOS.epos(name='radial_velocity', RV=True, MC=False, Msini=True)
```

```
|~| epos 3.0.0.dev4 |~|
```

```
Using random seed 322504493
Survey: None selected
```

Now we load the detected exoplanets and the survey completeness from the Mayor+ 2011 paper

```
[3]: obs, survey = EPOS.rv.Mayor2011()
      epos.set_observation(**obs, Verbose=False)
      epos.set_survey(**survey)
```

We are going to use a double broken power-law in mass and period to parametrize the intrinsic planet population. This function is pre-defined in the `EPOS.fitfunctions` module

```
[4]: epos.set_parametric(EPOS.fitfunctions.brokenpowerlaw2D)
```

Let's make an initial guess for each parameter. For the MCMC to run smoothly, we also define an upper and lower bound to some parameters with the `min` and `max` keywords.

The first parameter is a normalization parameter that defines the number of planets per star in the simulated range:

```
[5]: epos.fitpars.add('pps', 1.0, min=1e-3)
```

`brokenpowerlaw2D` uses 6 parameters, each indicated with the `is2D` keyword.

The first three parameters are the location of the break and the power-law indices before and after the break

```
[6]: epos.fitpars.add('P break', 1e3, min=100, max=7e3, is2D=True)
      epos.fitpars.add('a_P', 1.0, min=0, max=3, is2D=True)
      epos.fitpars.add('b_P', -0.5, min=-3, max=0, is2D=True)
```

The next three parameter define the planet mass distribution. We only use a single power-law in this example, so we fix the other two parameters.

```
[7]: epos.fitpars.add('M break', 10.0, fixed=True, is2D=True)
      epos.fitpars.add('a_M', 0.0, fixed=True, is2D=True)
      epos.fitpars.add('b_M', -0.5, dx=0.1, is2D=True)
```

Next, let's define the range of planet parameters that is simulated (`trim`) and the range compared to observations (`zoom`)

Units are period (days) and planet mass (earth mass)

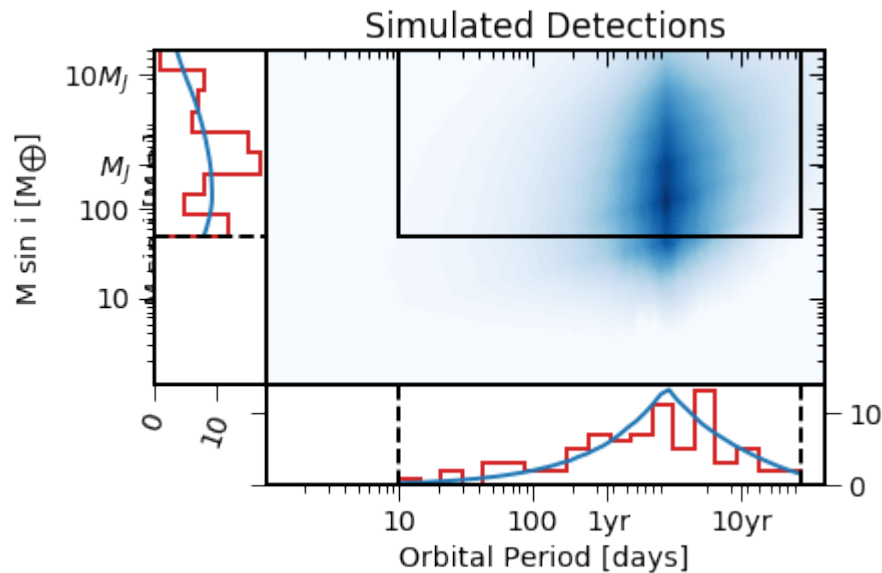
```
[8]: epos.set_ranges(xtrim=[1,1e5],ytrim=[1,1e5],xzoom=[10,1e4],yzoom=[50,1e4], Occ=True)
```

Now, let's run epos once to see what our initial distribution looks like and how it compares to observations

```
[9]: EPOS.run.once(epos)
EPOS.plot.periodradius.panels(epos, NB=True)
```

```
Preparing EPOS run...
6 fit parameters
```

```
Starting the first noMC run
Finished one noMC in 0.007 sec
```



Blue is the simulated distribution, red the detected planets.

Now let's calculate the occurrence rates for comparison

```
[10]: EPOS.occurrence.all(epos)
epos.plotpars['occrange']=[2e-4,2.]
EPOS.plot.parametric.oneD_x(epos, Occ=True, NB=True)
EPOS.plot.parametric.oneD_y(epos, Occ=True, NB=True)
```

Interpolating planet occurrence

```
x zoom bins
x: [10,1e+04], y: [1,1.7], n=0, comp=nan, occ=0
x: [10,1e+04], y: [1.7,2.6], n=1, comp=0.0027, occ=0.45
x: [10,1e+04], y: [2.6,4.1], n=3, comp=0.024, occ=0.17
x: [10,1e+04], y: [4.1,6.5], n=6, comp=0.079, occ=0.13
x: [10,1e+04], y: [6.5,10], n=7, comp=0.16, occ=0.061
x: [10,1e+04], y: [10,16], n=17, comp=0.19, occ=0.11
x: [10,1e+04], y: [16,26], n=14, comp=0.2, occ=0.097
x: [10,1e+04], y: [26,40], n=4, comp=0.23, occ=0.021
x: [10,1e+04], y: [40,64], n=7, comp=0.34, occ=0.028
x: [10,1e+04], y: [64,1e+02], n=9, comp=0.36, occ=0.034
x: [10,1e+04], y: [1e+02,1.6e+02], n=4, comp=0.55, occ=0.009
```

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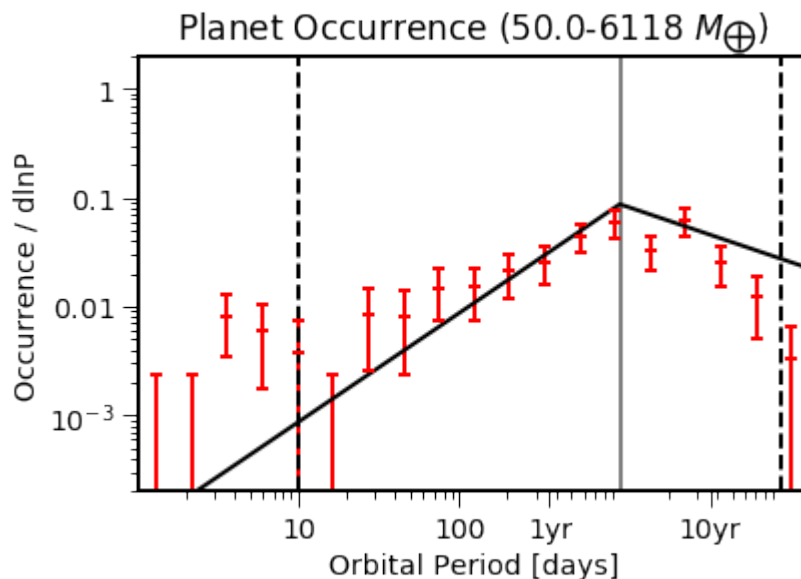
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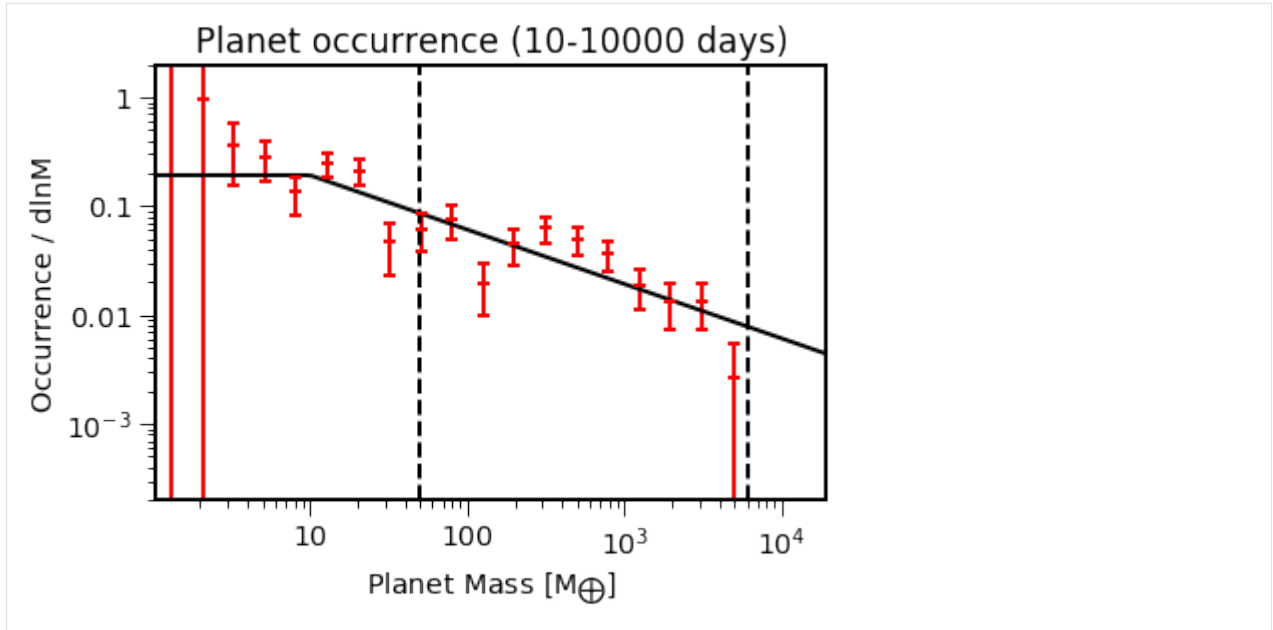
```
x: [10,1e+04], y: [1.6e+02,2.5e+02], n=8, comp=0.5, occ=0.02
x: [10,1e+04], y: [2.5e+02,4e+02], n=14, comp=0.61, occ=0.029
x: [10,1e+04], y: [4e+02,6.2e+02], n=13, comp=0.71, occ=0.022
x: [10,1e+04], y: [6.2e+02,9.9e+02], n=10, comp=0.76, occ=0.017
x: [10,1e+04], y: [9.9e+02,1.6e+03], n=6, comp=0.86, occ=0.0086
x: [10,1e+04], y: [1.6e+03,2.5e+03], n=5, comp=0.99, occ=0.0062
x: [10,1e+04], y: [2.5e+03,3.9e+03], n=5, comp=0.99, occ=0.0062
x: [10,1e+04], y: [3.9e+03,6.1e+03], n=1, comp=0.99, occ=0.0012
```

y zoom bins

```
x: [1.02,1.69], y: [50,6.1e+03], n=0, comp=nan, occ=0
x: [1.69,2.8], y: [50,6.1e+03], n=0, comp=nan, occ=0
x: [2.8,4.63], y: [50,6.1e+03], n=3, comp=0.89, occ=0.0041
x: [4.63,7.68], y: [50,6.1e+03], n=2, comp=0.83, occ=0.0031
x: [7.68,12.7], y: [50,6.1e+03], n=1, comp=0.64, occ=0.0019
x: [12.7,21.1], y: [50,6.1e+03], n=0, comp=nan, occ=0
x: [21.1,35], y: [50,6.1e+03], n=2, comp=0.58, occ=0.0043
x: [35,58.1], y: [50,6.1e+03], n=2, comp=0.7, occ=0.0041
x: [58.1,96.3], y: [50,6.1e+03], n=4, comp=0.72, occ=0.0074
x: [96.3,160], y: [50,6.1e+03], n=4, comp=0.65, occ=0.0076
x: [160,265], y: [50,6.1e+03], n=5, comp=0.68, occ=0.011
x: [265,439], y: [50,6.1e+03], n=7, comp=0.74, occ=0.013
x: [439,727], y: [50,6.1e+03], n=12, comp=0.71, occ=0.022
x: [727,1.21e+03], y: [50,6.1e+03], n=13, comp=0.64, occ=0.03
x: [1.21e+03,2e+03], y: [50,6.1e+03], n=8, comp=0.68, occ=0.016
x: [2e+03,3.31e+03], y: [50,6.1e+03], n=12, comp=0.59, occ=0.031
x: [3.31e+03,5.5e+03], y: [50,6.1e+03], n=6, comp=0.66, occ=0.013
x: [5.5e+03,9.11e+03], y: [50,6.1e+03], n=3, comp=0.6, occ=0.0061
x: [9.11e+03,1.51e+04], y: [50,6.1e+03], n=1, comp=0.72, occ=0.0017
```

```
/Users/mulders/anaconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:3118:
↳RuntimeWarning: Mean of empty slice.
    out=out, **kwargs)
/Users/mulders/anaconda3/lib/python3.7/site-packages/numpy/core/_methods.py:85:
↳RuntimeWarning: invalid value encountered in double_scalars
    ret = ret.dtype.type(ret / rcount)
```





The model population (black) looks reasonably close to the estimated occurrence rates (red).

Now let's run the MCMC chain to generate a planet population that better matches the data.

(This can take a long time, so the Saved keyword allows you to read in a previously saved run if it exists)

```
[11]: EPOS.run.mcmc(epos, nMC=1000, nwalkers=100, nburn=200, threads=20, Saved=True)
      EPOS.plot.periodradius.cdf(epos, NB=True)
```

```
Loading saved status from chain/radial_velocity/100x1000x5.npz
```

```
NOTE: Random seed changed: 1885962102 to 322504493
```

```
MC-ing the 30 samples to plot
```

```
Best-fit values
```

```
pps= 0.94 +0.237 -0.184
P break= 1.99e+03 +1.12e+03 -1.11e+03
a_P= 0.706 +0.324 -0.155
b_P= -1.06 +0.786 -1.29
b_M= -0.462 +0.0569 -0.0635
```

```
Starting the best-fit MC run
```

```
nobs=80 (x:88,y:73)
```

```
Goodness-of-fit
```

```
logp= -0.8
- p(n=80)=0.99
- p(x)=0.88
- p(y)=0.51
```

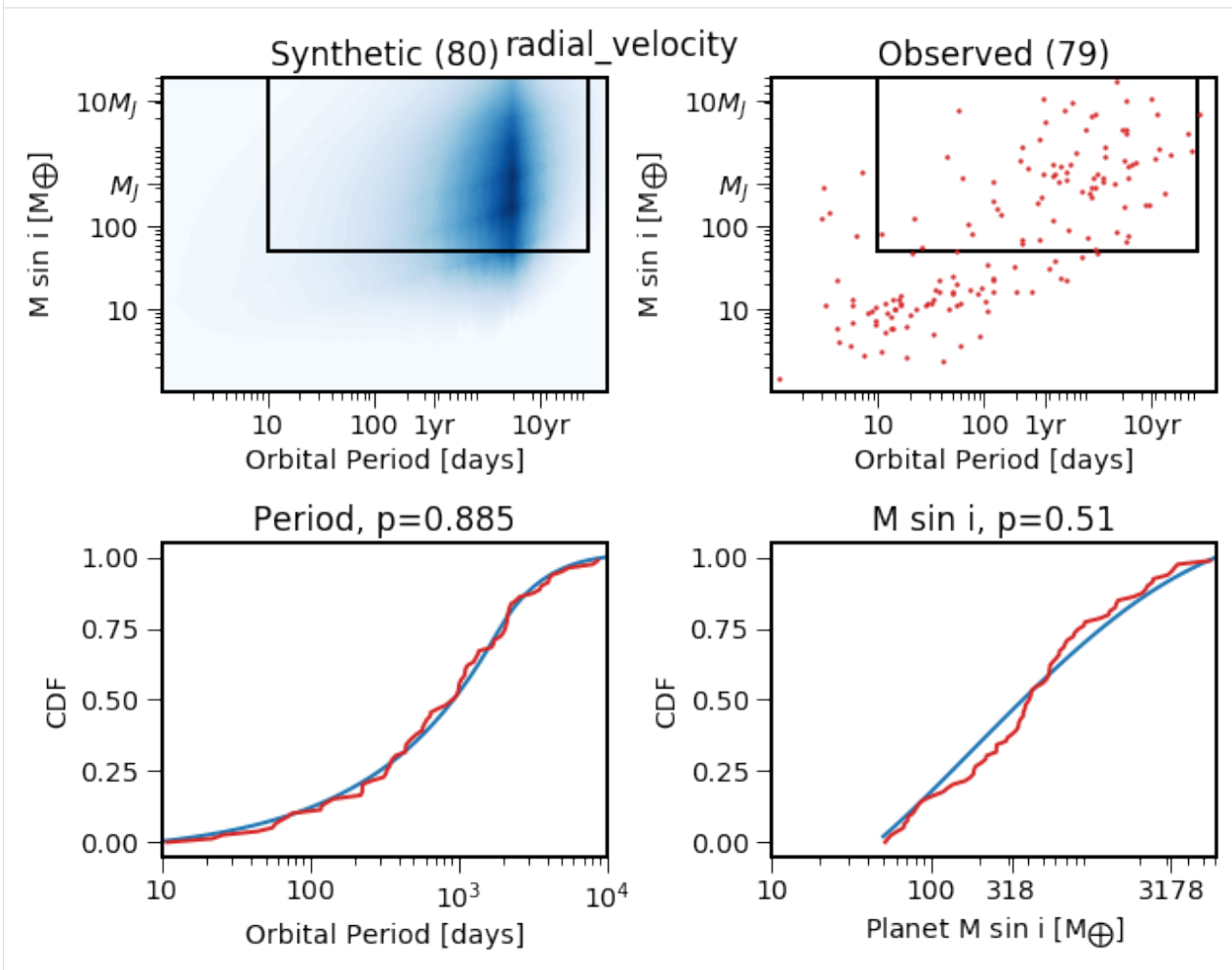
```
Akaike/Bayesian Information Criterion
```

```
- k=5, n=79
- BIC= 23.5
- AIC= 11.6, AICc= 9.5
```

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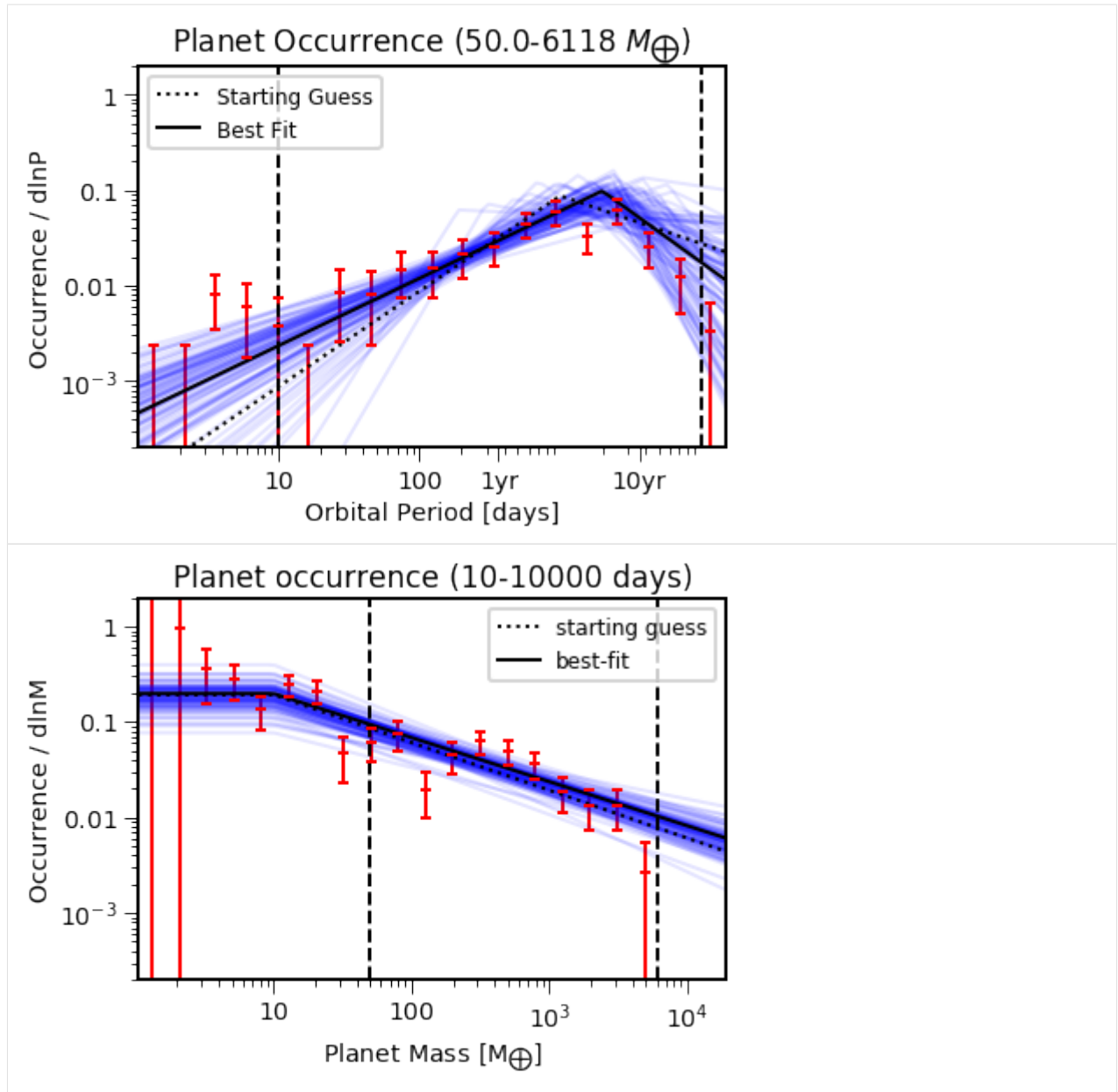
Observation comparison in 0.001 sec



The MCMC has minimized the distance between the simulated orbital period and Msini distribution (blue) and the observed planets (red).

Now let's take a look at the posterior planet occurrence rate distributions, and compare them with the occurrence rates.

```
[12]: EPOS.plot.parametric.oneD_x(epos, MCMC=True, NB=True, Occ=True)
      EPOS.plot.parametric.oneD_y(epos, MCMC=True, NB=True, Occ=True)
```



Now we have distribution that describes the occurrence in different regions of parameter space. Let's see what the prediction for directly imaged giant planets would be (1-10 au, 1-20 M_{jup})

```
[13]: Pbin= [365.24 * au**1.5 for au in [10,100.]]
Mbin= [Mj * EPOS.cgs.Mjup/EPOS.cgs.Mearth for Mj in [1,20]]
epos.set_bins(xbins=[Pbin], ybins=[Mbin])
EPOS.occurrence.parametric(epos)

posterior per bin
x: [1.15e+04,3.65e+05], y: [3.2e+02,6.4e+03], area=10.35, eta_0=0.014
gamma= 0.1% +0.2% -0.0%
eta= 0.6% +2.2% -0.5%
```

That's about 1%, consistent with the upper limits for FGK stars

3.9 Custom exoplanet survey

EPOS was designed to work with different exoplanet surveys.

This notebook shows how to load a (mock) exoplanet catalog and (mock) survey detection efficiency.

```
[1]: import EPOS
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats
```

initialize the EPOS class

```
[2]: epos= EPOS.epos(name='custom_survey')
```

```
|~| epos 3.0.1.dev3 |~|

Initializing 'custom_survey'

Using random seed 4144380222
Survey: None selected
```

3.9.1 Exoplanet catalog

Generate a mock exoplanet catalog with 131 planets detected in a survey of 18k stars

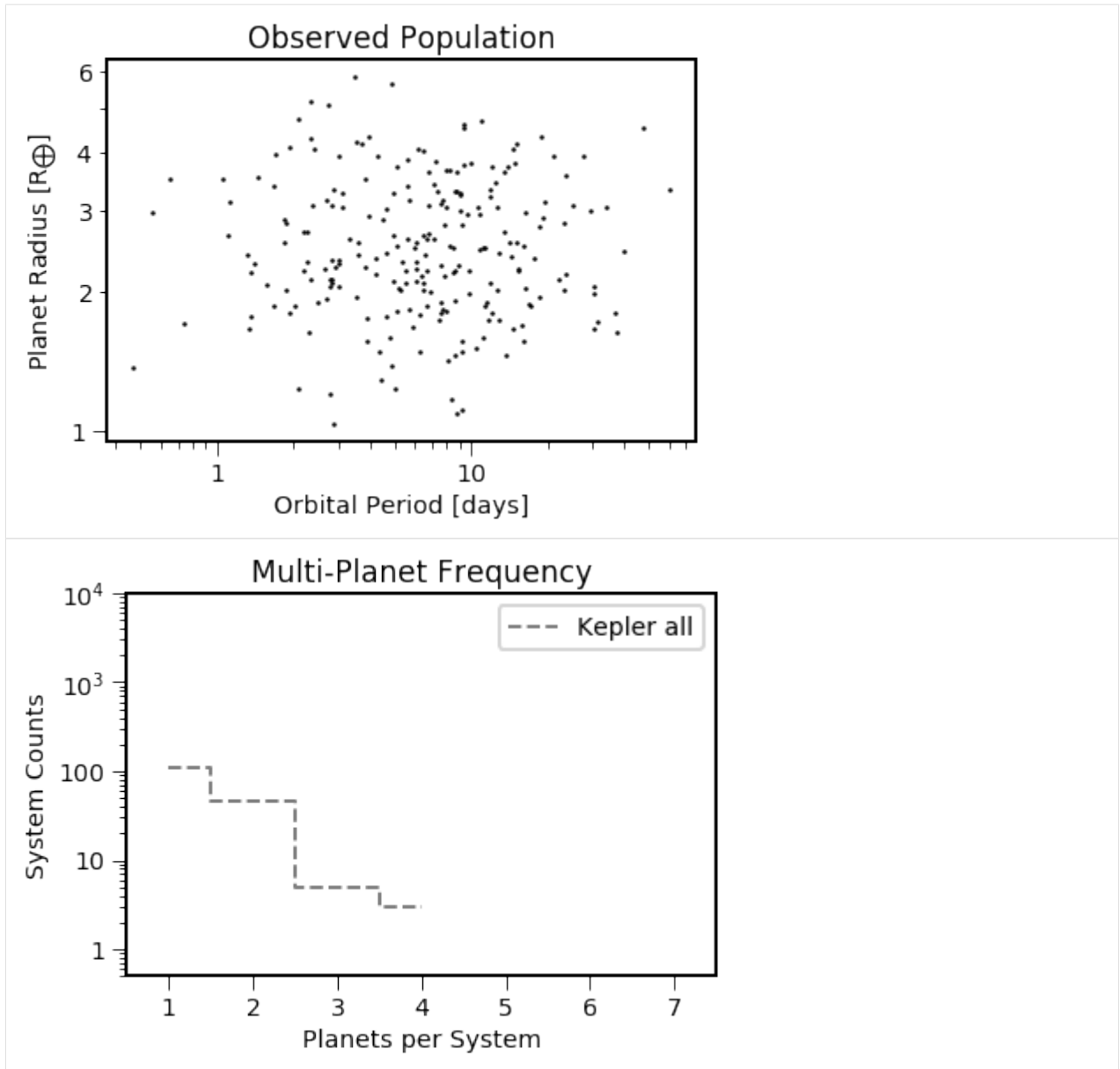
```
[3]: np.random.seed(76543)
nstars= 18000
npl= 231
period= 10.**np.random.normal(loc=0.8, scale=0.4, size=npl) # days
radius= 10.**np.random.normal(loc=0.4, scale=0.15, size=npl) # earth radii
starID= np.random.choice(np.arange(nstars/50), npl, replace=True) # star identifier_
→for each planet to identify multis (can be any format)
```

Load the mock catalog into EPOS

```
[4]: epos.set_observation(xvar=period, yvar=radius, starID=starID, nstars=nstars)
EPOS.plot.survey.observed(epos, NB=True, PlotBox=False)
EPOS.plot.multi.multiplicity(epos, NB=True)
```

```
Observations:
 18000 stars
  231 planets

110 singles, 55 multis
- single: 110
- double: 47
- triple: 5
- quad: 3
```



3.9.2 Detection efficiency

Generate a mock detection efficiency on a grid in period and radius

Note: the geometric detection efficiency factor is calculated by EPOS from the star mass and radius, so it does not need to be provided.

```
[5]: period_grid= np.geomspace(0.5, 300, 17)
    radius_grid= np.geomspace(0.3, 20, 19)
    Rstar= 1 # solar radius
    Mstar= 1 # solar mass

    P, R= np.meshgrid(period_grid, radius_grid, indexing='ij')
    detection_efficiency= scipy.stats.norm.cdf(np.log10(R),
```

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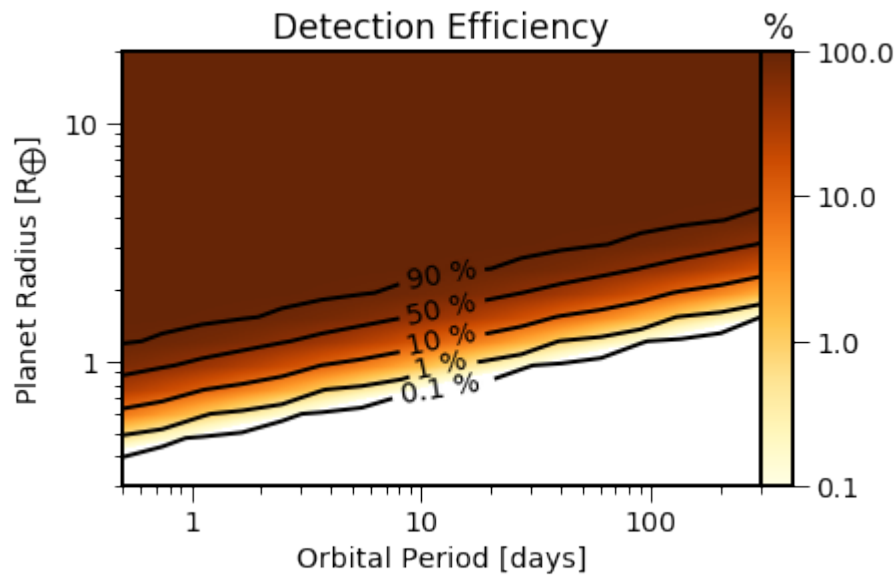
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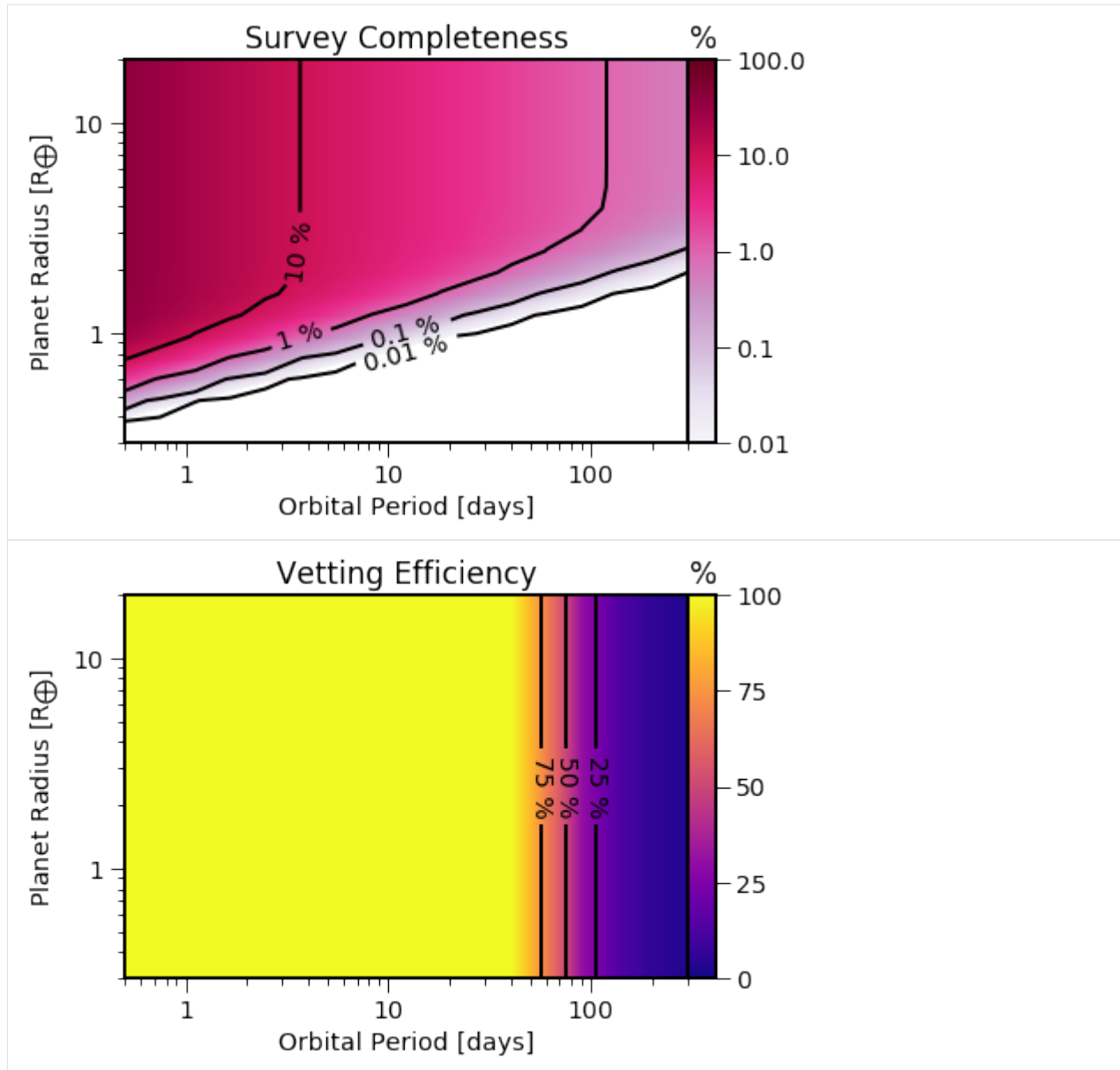
```
loc=0.0+0.2*np.log10(P), scale=0.1)

#vetting_efficiency=None # optional
vetting_efficiency= np.minimum(1, (P/50)**-2)
```

Load and display the survey detection efficiency

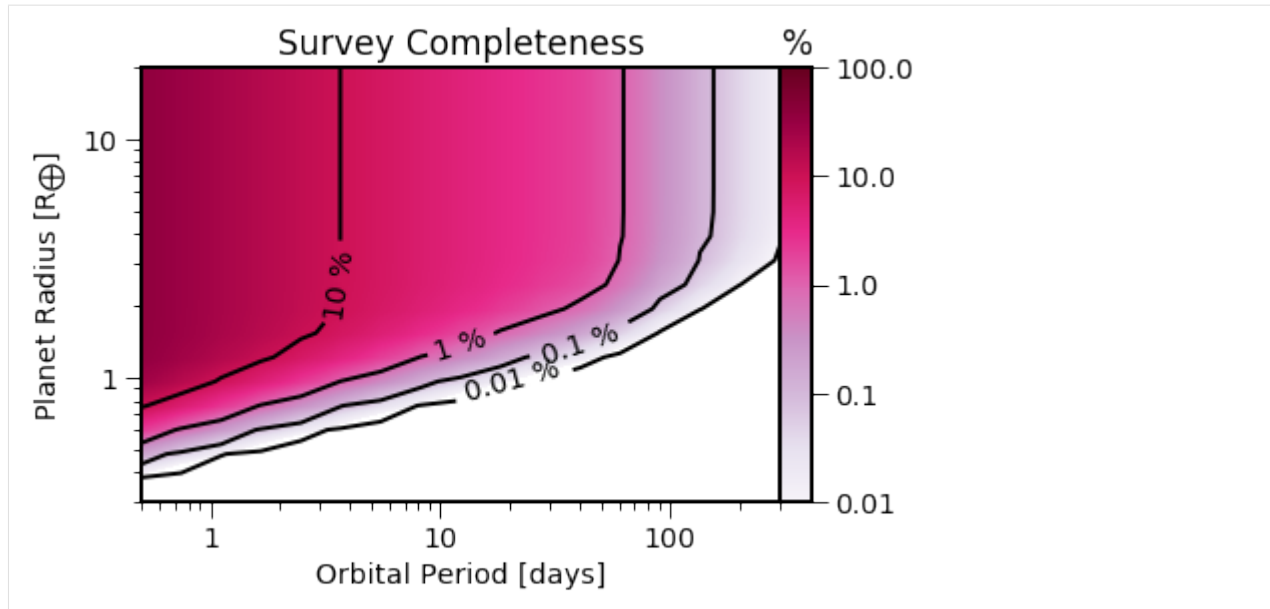
```
[6]: epos.set_survey(xvar= period_grid,
                    yvar= radius_grid,
                    eff_2D= detection_efficiency,
                    vet_2D= vetting_efficiency,
                    Rstar=Rstar, Mstar=Mstar
                    )
EPOS.plot.survey.completeness(epos, NB=True, Transit=True, Vetting=False,
                               PlotBox=False)
EPOS.plot.survey.completeness(epos, NB=True, Transit=False, Vetting=False,
                               PlotBox=False)
EPOS.plot.survey.vetting(epos, PlotBox=False, NB=True)
```





Show the combined completeness

```
[7]: EPOS.plot.survey.completeness(epos, NB=True, Vetting=True, PlotBox=False)
```



3.9.3 Occurrence Rates

Calculate Occurrence rates for the mock survey

First define bins where to calculate occurrence rates

```
[8]: epos.set_bins(xbins=[[5,20]], ybins=[[1.4,6]])
```

Define regions where observational comparisons are made (also used for some occurrence rate calculations)

```
[9]: epos.set_ranges(
    xtrim=[0,730],ytrim=[0.3,20.], # trim the detection efficiency grid
    xzoom=[1,100],yzoom=[1,4], # zoomed region for occurrence rates
    Occ=True) # calculate occurrence along period and radius grid
```

Calculate occurrence rates

```
[10]: EPOS.occurrence.all(epos)
```

Interpolating planet occurrence

Observed Planets

```
x: [5,20], y: [1.4,6], n=123, comp=0.05, occ=0.16
```

x zoom bins

```
x: [1,100], y: [0.3,0.38], n=0, comp=nan, occ=0
```

```
x: [1,100], y: [0.38,0.48], n=0, comp=nan, occ=0
```

```
x: [1,100], y: [0.48,0.6], n=0, comp=nan, occ=0
```

```
x: [1,100], y: [0.6,0.76], n=0, comp=nan, occ=0
```

```
x: [1,100], y: [0.76,0.96], n=0, comp=nan, occ=0
```

```
x: [1,100], y: [0.96,1.2], n=5, comp=0.02, occ=0.039
```

```
x: [1,100], y: [1.2,1.5], n=11, comp=0.036, occ=0.023
```

```
x: [1,100], y: [1.5,1.9], n=39, comp=0.062, occ=0.091
```

```
x: [1,100], y: [1.9,2.4], n=61, comp=0.08, occ=0.066
```

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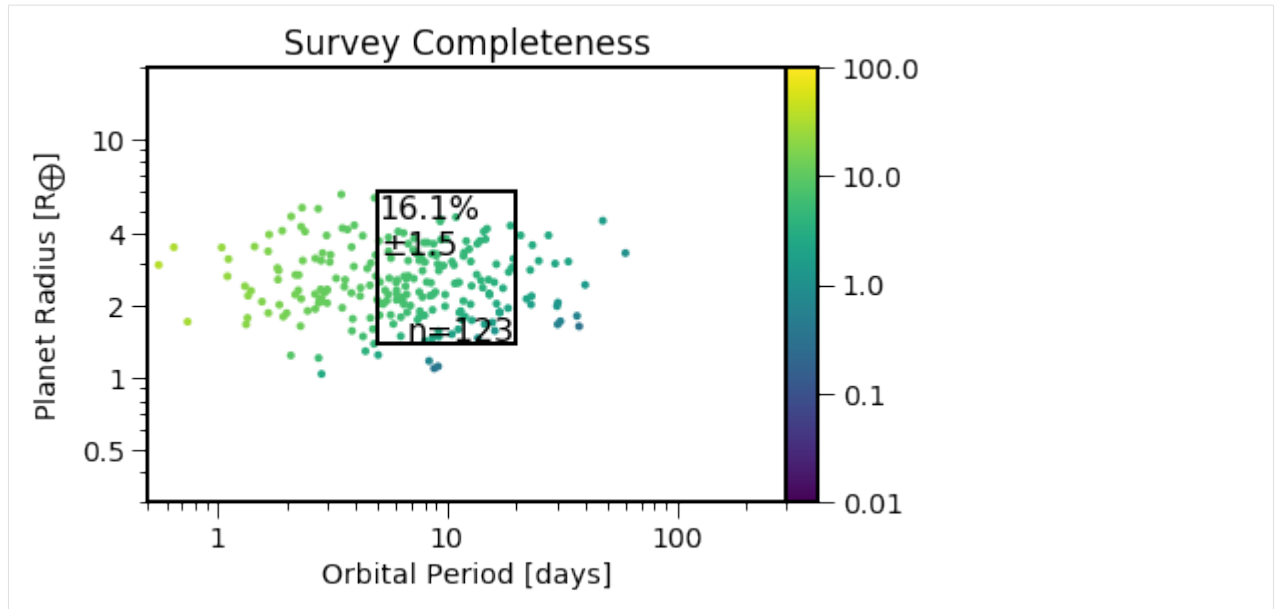
```
x: [1,100], y: [2.4,3.1], n=49, comp=0.074, occ=0.049
x: [1,100], y: [3.1,3.9], n=37, comp=0.077, occ=0.038
x: [1,100], y: [3.9,4.9], n=21, comp=0.082, occ=0.021
x: [1,100], y: [4.9,6.2], n=4, comp=0.11, occ=0.0021
x: [1,100], y: [6.2,7.9], n=0, comp=nan, occ=0
x: [1,100], y: [7.9,9.9], n=0, comp=nan, occ=0
x: [1,100], y: [9.9,13], n=0, comp=nan, occ=0
x: [1,100], y: [13,16], n=0, comp=nan, occ=0
x: [1,100], y: [16,20], n=0, comp=nan, occ=0

y zoom bins
x: [0.5,0.746], y: [1,4], n=3, comp=0.32, occ=0.00052
x: [0.746,1.11], y: [1,4], n=2, comp=0.23, occ=0.00049
x: [1.11,1.66], y: [1,4], n=8, comp=0.19, occ=0.0023
x: [1.66,2.47], y: [1,4], n=17, comp=0.15, occ=0.0066
x: [2.47,3.69], y: [1,4], n=24, comp=0.11, occ=0.014
x: [3.69,5.51], y: [1,4], n=27, comp=0.076, occ=0.022
x: [5.51,8.21], y: [1,4], n=44, comp=0.062, occ=0.041
x: [8.21,12.2], y: [1,4], n=39, comp=0.042, occ=0.085
x: [12.2,18.3], y: [1,4], n=24, comp=0.032, occ=0.049
x: [18.3,27.2], y: [1,4], n=11, comp=0.027, occ=0.023
x: [27.2,40.6], y: [1,4], n=10, comp=0.014, occ=0.063
x: [40.6,60.6], y: [1,4], n=1, comp=0.01, occ=0.0054
x: [60.6,90.4], y: [1,4], n=0, comp=nan, occ=0
x: [90.4,135], y: [1,4], n=0, comp=nan, occ=0
x: [135,201], y: [1,4], n=0, comp=nan, occ=0
x: [201,300], y: [1,4], n=0, comp=nan, occ=0
```

```
/Users/mulders/anaconda3/lib/python3.7/site-packages/numpy/core/fromnumeric.py:3257:
↳RuntimeWarning: Mean of empty slice.
    out=out, **kwargs)
/Users/mulders/anaconda3/lib/python3.7/site-packages/numpy/core/_methods.py:161:
↳RuntimeWarning: invalid value encountered in double_scalars
    ret = ret.dtype.type(ret / rcount)
```

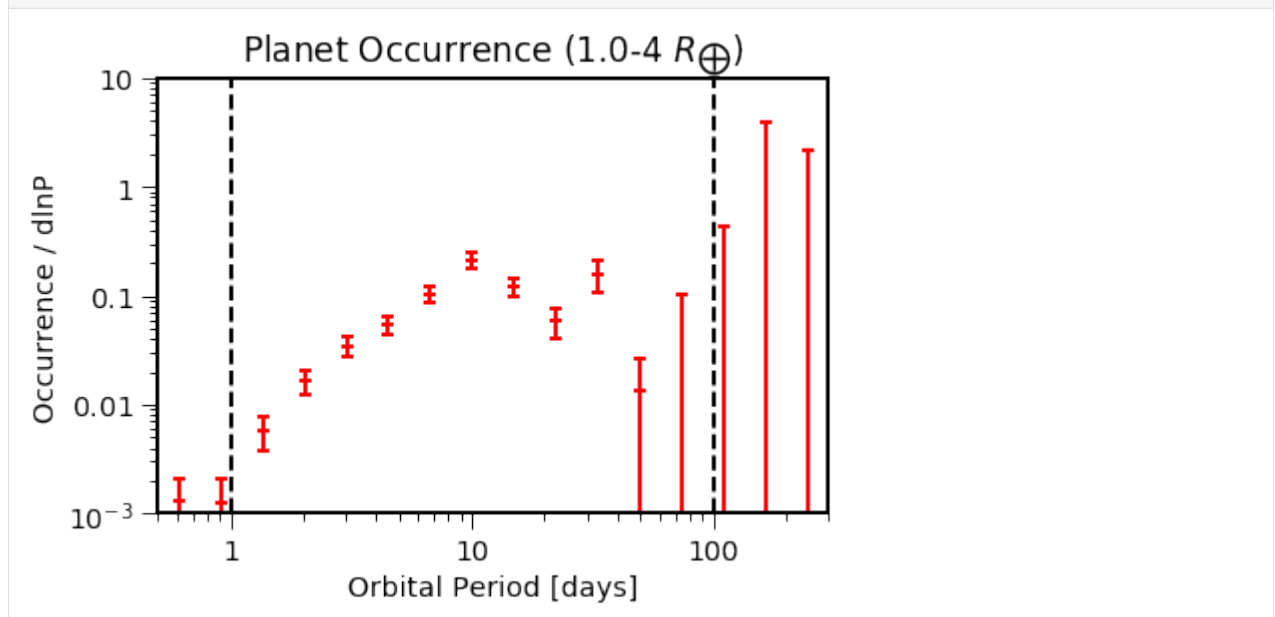
Plot the planet catalog with color-coded completeness

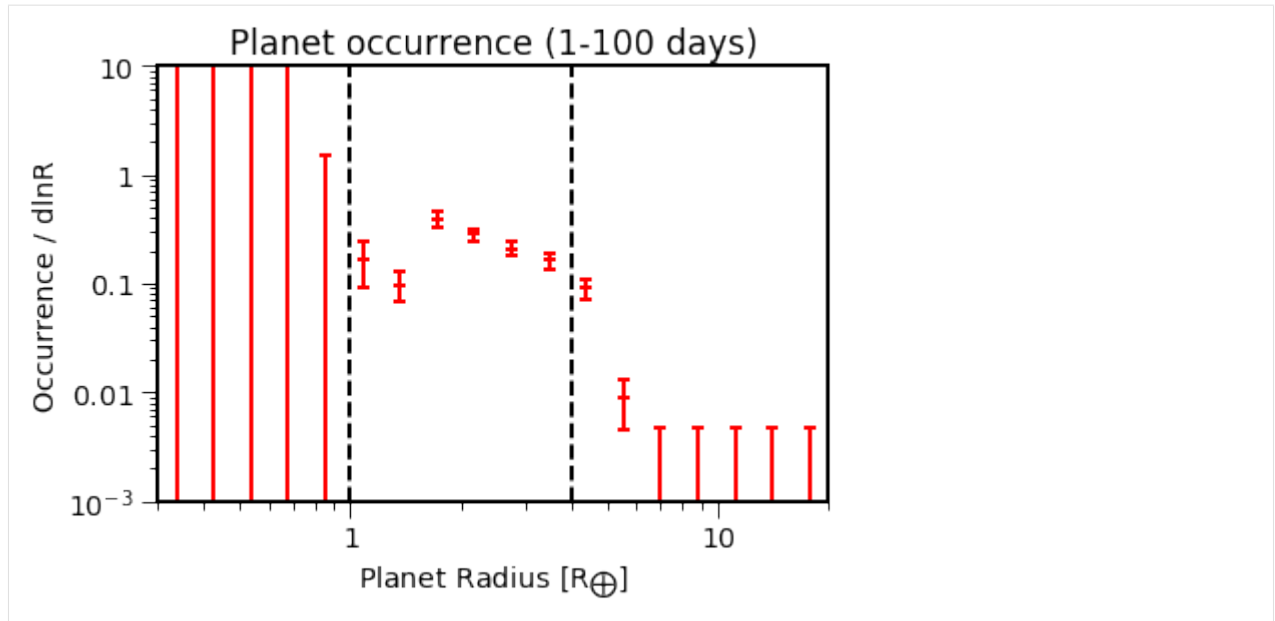
```
[11]: EPOS.plot_occurrence.colored(epos, Bins=True, NB=True)
```



And plot the occurrence rates as function of period and radius

```
[12]: EPOS.plot.parametric.oneD_x(epos, NB=True, Occ=True, Init=False)
      EPOS.plot.parametric.oneD_y(epos, NB=True, Occ=True, Init=False)
```





You can now continue to estimate parametric distributions of planet occurrence or planetary system architectures as described in the [other notebooks](#)

3.10 API

This generates the API, showing some documented functions

(this is a link to [EPOS.epos](#))

3.10.1 The epos class

```
class EPOS.epos (name, Debug=False, seed=True, title=None, RV=False, Norm=False, MC=True,
                  Msini=False, survey=None)
```

The epos class

Description: Initialize

Parameters

- **name** (*str*) – name to use for directories
- **survey** (*str*) – Survey data to load. ['Kepler', 'RV']. Default None
- **RV** (*bool*) – Compare to radial velocity instead of transits
- **MC** (*bool*) – Generate planet population by random draws
- **Msini** (*bool*) – Convert the planet mass distribution into an Msini distribution
- **Debug** (*bool*) – Log more output for debugging
- **seed** (*int*) – Same random number for each simulation? True, None, or int
- **Norm** (*bool*) – normalize pdf (deprecated?)

name
 name
Type str

plotdir
 plot directory
Type str

RV
 Compare to Radial Velocity instead of transit data
Type bool

Multi
 Do multi-planet statistics
Type bool

RandomPairing
 multis are randomly paired
Type bool

Parametric
 parametric planet population?
Type bool

Debug
 Verbose logging
Type bool

seed
 Random seed, can be any of int, True, or None

jsondir = None
 EPOS mode

plotpars = None
 Load Default Settings for each Survey

set_bins (*xbins=[[1, 10]], ybins=[[1, 10]], xgrid=None, ygrid=None, Grid=False, MassRadius=False*)
 Initialize period-radius (or mass) bins for occurrence rate calculations
Description: Bins can be generated from a grid, f.e. `xgrid=[1,10,100]`, or from a list of bin edges, f.e. `xbins=[[1,10],[10,100]]`

Parameters

- **xbins** (*list*) – (list of) period bin edges
- **ybins** (*list*) – (list of) radius/mass bin edges
- **xgrid** (*list*) – period bin in interfaces
- **ygrid** (*list*) – radius/mas bin interfaces
- **Grid** (*bool*) – If true, create a 2D grid from bins: `nbins = nx * ny`. If false, pair x and y bins: `nbins == nx == ny`

set_bins_poly (*polys, labels=None*)
 Initialize polygonic bins for occurrence rate calculations

Description: each polygone is a Nx2 numpy array of (x,y) coordinates

Parameters `polys` (*list*) – (list of) polygones

set_observation (*xvar, yvar, starID, nstars=168620.0, radiusError=0.1, score=None, tdur=None, Verbose=True*)
Observed planet population

Parameters

- **xvar** – planet orbital period [list]
- **yvar** – planet radius or M sin i [list]
- **ID** – planet ID [list]
- **nstars** – number of stars surveyed

Note: Some pre-defined planet populations from Kepler can be generated from `EPOS.kepler.dr25()`

set_parametric (*func*)

Define a parametric function to generate the planet size-period distribution

Description: Function should be callable as `func(X, Y, *fitpars2d)` with `X(np.array)`: period `Y(np.array)`: size (radius or mass) The list of fit parameters `fitpars2d` will be constructed from parameters added using `EPOS.fitparameters.add()` with `is2D=True`

Note: Some pre-defined functions can be found in `EPOS.fitfunctions`

Parameters `func` (*function*) – callable function

set_survey (*xvar, yvar, eff_2D, Rstar=1.0, Mstar=1.0, vet_2D=None*)

Survey detection efficiency (completeness) :param xvar: planet orbital period grid [list] :param yvar: planet radius or M sin i grid [list] :param eff_2D: 2D matrix of detection efficiency :param Rstar: stellar radius, for calculating transit probability :param Mstar: stellar mass, for period-semimajor axis conversion

Note: Some pre-defined detection efficiencies from Kepler can be generated from `EPOS.kepler`

class `EPOS.fitparameters`

Holds the fit parameters. Usually initialized in `epos.fitpars`

add (*key, value, fixed=False, min=-inf, max=inf, dx=None, text=None, is2D=False, isnorm=False*)
Add a fit parameter

Parameters

- **key** (*str*) – fit parameter dictionary key
- **value** (*float*) – starting guess
- **fixed** (*bool*) – keep this parameter fixed
- **min** (*float*) – lower bound
- **max** (*float*) – upper bound
- **dx** (*float*) – initial dispersion for MCMC

- **text** (*str*) – plot safe name?
- **is2D** (*bool*) – use this parameter in the 2D parametric `EPOS.fitfunctions()`
- **isnorm** (*bool*) – this parameter is the normalization factor for the number of planet per star `EPOS.fitfunctions()`

3.10.2 Fit parameters

class `EPOS.fitparameters`

Holds the fit parameters. Usually initialized in `epos.fitpars`

add (*key, value, fixed=False, min=-inf, max=inf, dx=None, text=None, is2D=False, isnorm=False*)
Add a fit parameter

Parameters

- **key** (*str*) – fit parameter dictionary key
- **value** (*float*) – starting guess
- **fixed** (*bool*) – keep this parameter fixed
- **min** (*float*) – lower bound
- **max** (*float*) – upper bound
- **dx** (*float*) – initial dispersion for MCMC
- **text** (*str*) – plot safe name?
- **is2D** (*bool*) – use this parameter in the 2D parametric `EPOS.fitfunctions()`
- **isnorm** (*bool*) – this parameter is the normalization factor for the number of planet per star `EPOS.fitfunctions()`

CHAPTER 4

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EPOS was developed as part of the of the [Earths in Other Solar Systems](#) project, a [NASA/NExSS](#) program

Please cite the papers the two EPOS papers ([Mulders et al. 2018](#); [2019](#)) if you use epos. You can also cite the github repository directly

List of Publications

Mulders et al. 2018 The Exoplanet Population Observation Simulator. I - The Inner Edges of Planetary Systems

Pascucci et al. 2018 A Universal Break in the Planet-to-star Mass-ratio Function of Kepler MKG Stars

Kopparapu et al. 2018 Exoplanet Classification and Yield Estimates for Direct Imaging Missions

Fernandes et al. 2019 Hints for a Turnover at the Snow Line in the Giant Planet Occurrence Rate

Mulders et al. 2019 The Exoplanet Population Observation Simulator. II - Population Synthesis in the Era of Kepler

Pascucci et al. 2019 The impact of stripped cores on the frequency of Earth-size planets in the habitable zone

CHAPTER 6

Version Notes:

- 1.0.1** first public release
- 1.0.2** pip installable version
- 1.1.0** radial velocity without Monte Carlo
- 2.0.2** planet formation models
- 3.0.x** python 3 / jupyter compatible version

CHAPTER 7

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