QUANTIFYING THE EVIDENCE FOR A PLANET IN RADIAL VELOCITY DATA

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arXiv:1806.04683 github.com/EPRV3EvidenceChallenge



Radial Velocity Observations





5 parameters describe a planet's RV signature

orbital period orbital eccentricity argument of pericenter orbital phase mass

What does it mean to "discover" a planet?

Frequentist Approach

Reject the null hypothesis that a model without a planet could reasonably explain the data

conceptually difficult, computationally easy

Bayesian Approach

Evidence (i.e., marginalized likelihood) for a model with the planet is much greater than alternative models without the planet

conceptually easy, computationally difficult

Further reading jakevdp.github.io Frequentism & Bayesianism Part 5: Model Selection

Methods for dealing with new RV challenges

Computing the "evidence"

$$\mathcal{Z} \equiv p(d|\mathcal{M}) = \int p(\theta|\mathcal{M})p(d|\theta,\mathcal{M})d\theta$$



Dumusque 2016 Dumusque+ 2017 Thermodynamic integration (HD208487, Gregory 2007)

Nested sampling / MultiNest (GJ667C, Feroz & Hobson 2014)

Geometric path Monte Carlo (GJ581, Hou+ 2014)

Transdimensional MCMC w/ nested sampling (v Oph, Brewer & Donovan 2015)

Importance sampling (GJ876, Nelson+ 2016; HD9174, Jenkins+ 2017)



Evidence Challenge

How accurately/precisely can one compute the "evidence" for {0, 1, 2, 3} planets in RV data, given a set of priors and likelihood function?

$$\mathcal{Z} \equiv p(\boldsymbol{d}|\mathcal{M}) = \int p(\boldsymbol{\theta}|\mathcal{M}) p(\boldsymbol{d}|\boldsymbol{\theta}, \mathcal{M}) \boldsymbol{d\theta}_{July 24, 2018}$$

How is this NOT Xavier Dumusque's RV Fitting Challenge?





Evidence Challenge

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Evidence Challenge

what methods are good at finding "real" planets in data

data: RVs and activity indicators (FWHM, logR'{hk}, BIS span)

prize: 30 year old Tawny Port wine

what methods are good at computing an accurate "evidence"

data: just RVs

prize: knowledge

Four Questions of the Evidence Challenge

1. What is the dispersion in \mathcal{Z} ?

2. Does the uncertainty in \mathcal{Z} accurately reflect the observed dispersion?

3. How does (1) and (2) affect our ability to favor n vs n-1 planets?

4. What methods should be recommended/avoided/further improved?

EPRV3 Evidence Challenge

We generate 6 RV datasets. Each dataset contained **two** planets with varying levels of detectability.

Data are drawn from a multivariate Gaussian with correlated observations, measured uncertainties, and an additional unknown white noise term (i.e., jitter).

We use a quasi-periodic kernel (Rajpaul+ 2015)...

$$K_{i,j} = \alpha^2 exp \left[-\frac{1}{2} \left\{ \frac{\sin^2[\pi(t_i - t_j)/\tau]}{\lambda_p^2} + \frac{(t_i - t_j)^2}{\lambda_e^2} \right\} \right]$$

...with known hyperparameters α , λ_p , λ_e , and τ .

EPRV3 Evidence Challenge

Two sets of priors



Narrow



EPRV3 Evidence Challenge

More details and results at: github.com/EPRV3EvidenceChallenge/

Methods teams submitted:

Frequentist

BIC

leave-one-out cross-validation time-series cross-validation

Bayesian Chib's approximation Laplace approximation Laplace approximation + I1 periodogram Perrakis estimator importance sampling + MCMC importance sampling + variational Bayes nested sampling (MultiNest) nested sampling + MCMC diffusive nested sampling (DNest4)

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0-planet model (2 parameters)



Dataset #1

0-planet model (2 parameters)



0-planet model (2 parameters)



1-planet model (7 parameters)



Sagan Workshop

1-planet model (7 parameters) narrow priors



2-planet model (12 parameters) narrow priors



Sagan Workshop

3-planet model (17 parameters) narrow priors



Four Questions of the Evidence Challenge

1. What is the dispersion in \mathcal{Z} ?

model:0 planets---> 1 planet2 planets---> 3 planetsdispersion:~few~OOM~few to several OOMs

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Internal estimates of one evidence calculation underestimate the uncertainty. Monte Carlo methods seem to provide reasonable uncertainties.

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...and can I somehow cram all this information into a single figure?

datasets models priors methods logZ or logOddsRatio





choice of prior













(n)v(n-1), i.e.,
$$\frac{p(\mathcal{M}_n|d)}{p(\mathcal{M}_{n-1}|d)}$$





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Importance and nested sampling methods mostly arrive at the same conclusions. Cheaper methods are relatively overconfident in estimated odds ratios.

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Broad

Narrow

Table 4. Number of likelihood evaluations (n_d) reported to calculate $\log Z$

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Evidence Challenge Conclusions and Links

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arXiv:1806.04683

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github.com/EPRV3EvidenceChallenge

Supplemental Slides















What different methods say about the evidence estimate



Efficiently computing the FML for thousands of datasets

Systematic mischaracterization of exoplanetary system dynamical histories from a model degeneracy near mean-motion resonance

John H. Boisvert, Benjamin E. Nelson, Jason H. Steffen

(Submitted on 26 Apr 2018)

There is a degeneracy in the radial velocity exoplanet signal between a single planet on an eccentric orbit and a two-planet system with a period ratio of 2:1. This degeneracy could lead to misunderstandings of the dynamical histories of planetary systems as well as measurements of planetary abundances if the correct architecture is not established. We constrain the rate of mischaracterization by analyzing a sample of 60 non-transiting, radial velocity systems orbiting main sequence stars from the NASA Exoplanet Archive (NASA Archive) using a new Bayesian model comparison pipeline. We find that 15 systems (25% of our sample) show compelling evidence for the two-planet case with a confidence level of 95%.

Comments: 4 pages, 4 figures, and a two-page appendix containing 2 figures Subjects: Earth and Planetary Astrophysics (astro-ph.EP) Cite as: arXiv:1804.10143 [astro-ph.EP] (or arXiv:1804.10143v1 [astro-ph.EP] for this version)

arXiv:1804.10143

The Laplace Approximation

Want to solve...

$$\int d\mathbf{x} \exp[\mathbf{f}(\mathbf{x})]$$

Taylor expand around x_0 , the location of the global mode...

$$f(\mathbf{x}) \simeq f(\mathbf{x}_o) + \frac{1}{2} \sum_{a,b} \frac{\partial^2 f}{\partial x_a \partial x_b} (\mathbf{x} - \mathbf{x}_o)^2$$

Approximate integral as...

$$\int d\mathbf{x} \exp[f(\mathbf{x})] \simeq \left[\frac{(2\pi)^2}{|\det H(\mathbf{x}_o)|}\right]^{1/2} \exp[f(\mathbf{x}_o)]$$