CONQUERING EXOPLANET SIGNALS

EMPEROR

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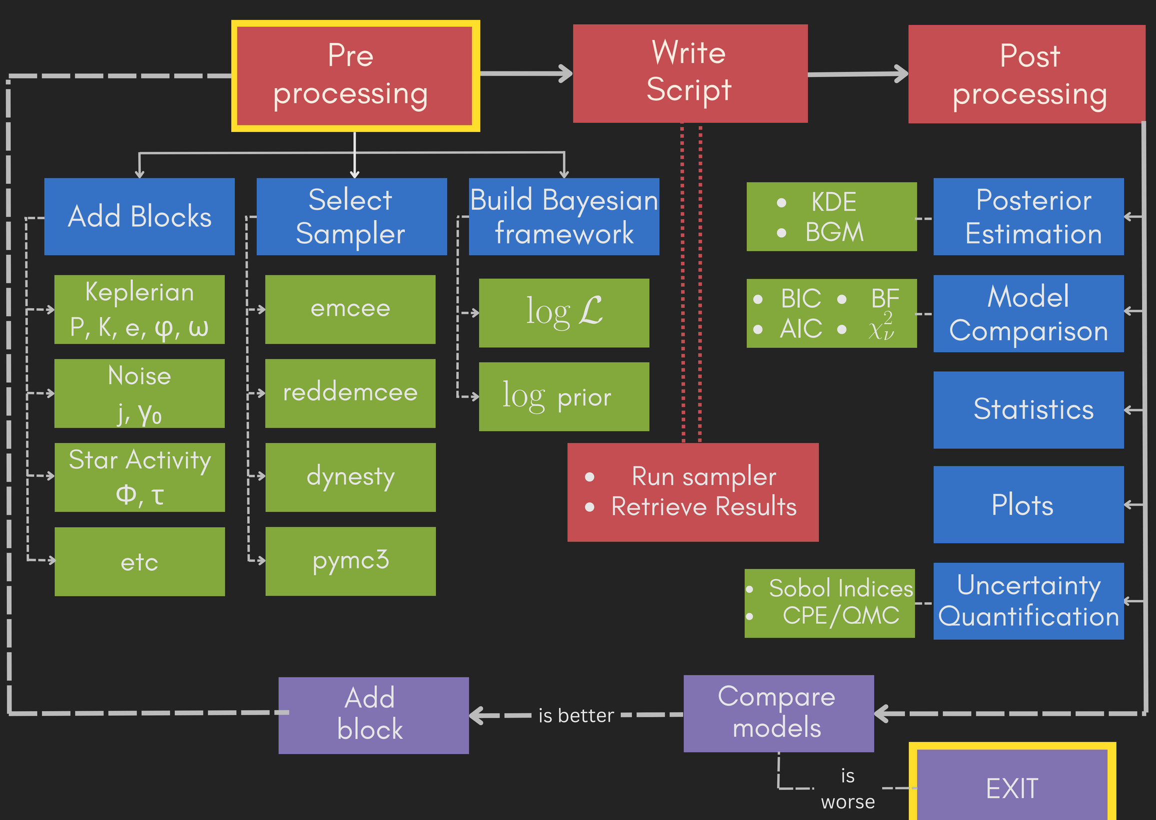
EPISODE I
THE SAMPLER MENACE

EMPEROR is a highly flexible Python-based algorithm that automatically searches for Keplerian signals in radial velocity time-series in a Bayesian framework, featuring:

- **Native Keplerian and noise models**
- **Adaptative Parallel Tempering MCMC sampler**
- **Model Comparison**
- **Posterior Estimation**
- **Statistical Analysis**
- **Uncertainty Quantification**

All in a modular package, easy to upgrade and easier to use.



EMPEROR builds blocks. A block contains a model, alongside parameters and metadata.

After selecting a sampler, a **temporary script** is created, where **each block hard-codes** it's own data along the sampling routine. This enables true multi-processing, for maximum efficiency.

Posteriors are estimated with Gaussian Mixtures or KDE. If the model is better than the previous one, add a block, use posteriors as priors. **Repeat.**

EPISODE IV
THE BENCHMARK STRIKES BACK

As a first benchmark we want to showcase the problem of the Gaussian shells. It's familiar, **scalable and analytically tractable**.

We compared our **APT** algorithm with *dynesty's* **Dynamic NS**.

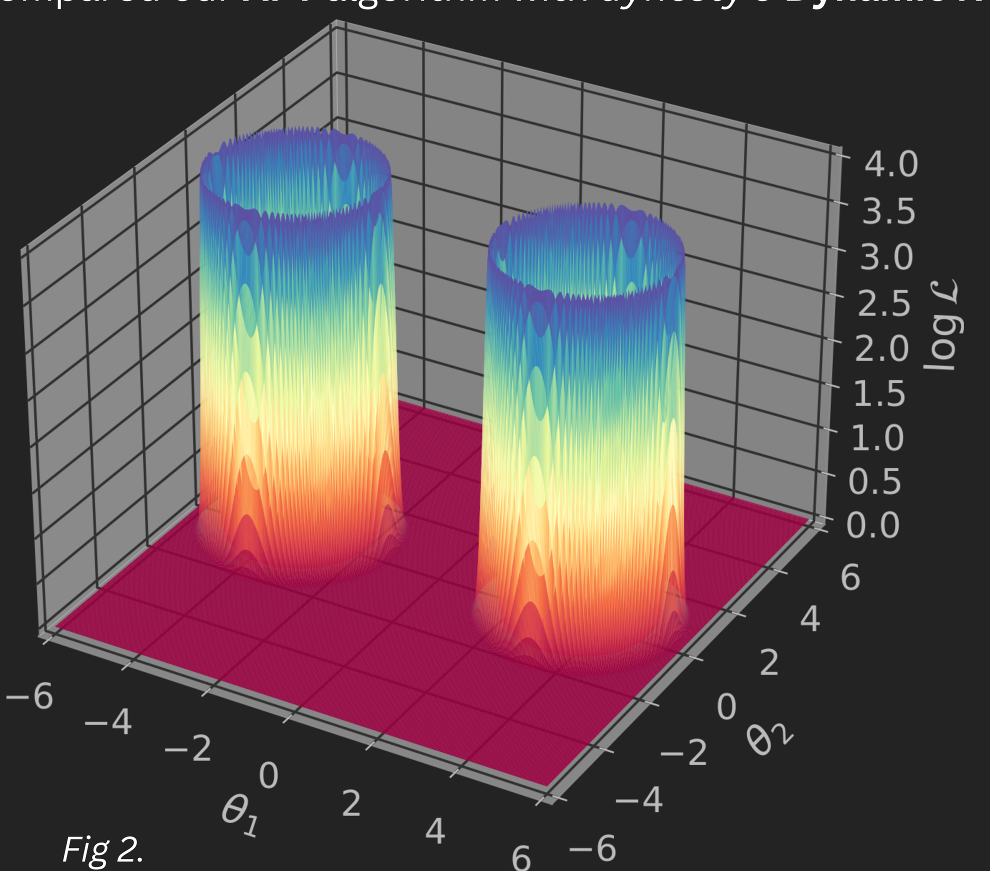


Fig 2. Loglikelihood evaluations of a 2D Gaussian shell with a tight grid.

We notice that APT

- not so tight constraints on Z (*!)
- iterations are ~15 times faster at d=2.
- About ~1.3 faster at d=20

And DNS:

- precise Z estimations
- speeds up with Ndim (!*)
- A bit slow overall

	reddemcee			dynesty		
N dim	Time	N eval	Nits	Time	N eval	Nits
2	54.59	2200	40.3	59.52	170.70	2.86
5	62.59	2200	35.15	50.12	199.40	3.96
20	93.29	2200	23.58	60.64	1107.63	18.27

*Table 1. Performance comparison for Gaussian Shells. **Yellow** is better.*
Time in (seconds)
N eval (x 1000)
Nits (x 1000/seconds)

N dim	Analytical log(Z)	reddemcee log(Z)	dynesty log(Z)
2	-1.75	-1.77 ± 0.56	-1.78 ± 0.04
5	-5.67	-6.11 ± 1.48	-5.66 ± 0.06
20	-36.09	-29.57 ± 6.61	-36.05 ± 0.15

Table 2. log (Z) estimation with errors.

EPISODE II
ATTACK OF THE NESTED SAMPLER

Nested samplers have the ability to accurately estimate the **marginal likelihood** or **evidence (Z)**, in contrast to MCMC.

Any Bayesian implementation needs to consider:

- The **time** they take to run
- The **accuracy** of the estimations
- How to make such methods fully **automated**

Nested Sampling	MCMC
+ better at evidence estimation + good with multi-modal distributions	+ better at posterior estimation + fast iterations
- scales poorly with dimensions - scales poorly with prior volume.	- inefficient with multi-modal distributions - poor evidence estimation

EPISODE V
RETURN OF THE 51PEG

As our second benchmark, we use **51Peg** to compare exoplanetary performance. We make the runs **without any hand-tinkering**. A **wide prior volume** is used (eg, period $\sim\mathcal{U}$[tmin, tmax]), default batches, walkers, temperatures, etc.

- After 4 hours of running, DNS **didn't converge**
- **Hard boundaries** were manually added for DNS and re-run. Period $\sim\mathcal{U}$ (3, 5), Amplitude $\sim\mathcal{U}$ (40, 60) and Eccentricity $\sim\mathcal{U}$ (0, 0.1), it converged after ~1.5h

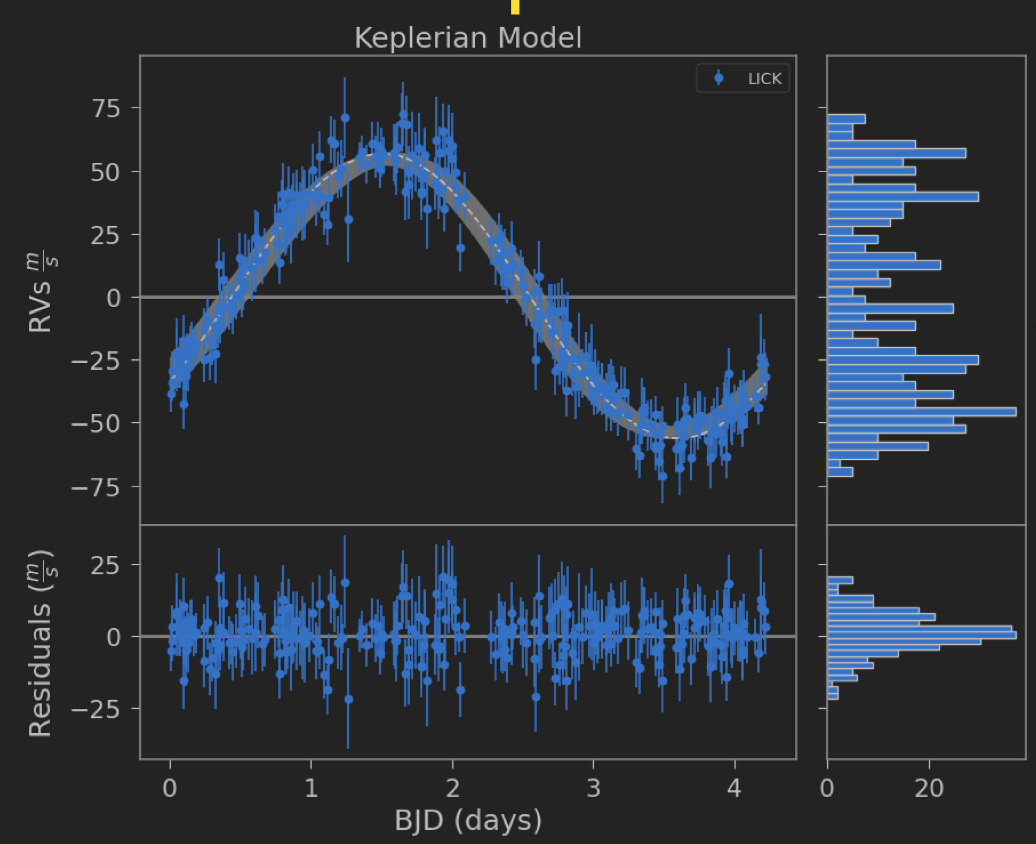


Fig 3. Phase-folded RV. UQ Model calculated with chaos polynomial expansions from the posteriors.

	reddemcee	dynesty*	Butler 06
Time	193.12	4939.41	
Nit/s	2.59	0.88	
MLL	-188.47	-198.73	
Z	-194.34 ± 36.65	-218.80 ± 3.46	
P (d)	$\mathcal{N}$ (4.23, 0.01)	$\mathcal{N}$ (4.17, 0.35)	4.23±0.00
K (m/s)	$\mathcal{N}$ (50.73, 2.44)	$\mathcal{N}$ (48.96, 5.63)	55.94±0.69
Ecc	$\mathcal{N}$ (0.05, 0.02)	$\mathcal{N}$ (0.05, 0.03)	0.01
a (AU)	$\mathcal{N}$ (0.05, 0.00)	$\mathcal{N}$ (0.05, 0.00)	0.05 ± 0.00
MM (MJ)	$\mathcal{N}$ (0.44, 0.02)	$\mathcal{N}$ (0.42, 0.05)	0.47 ± 0.04
Jitter	$\mathcal{N}$ (14.48, 5.34)	$\mathcal{N}$ (37.16, 16.35)	11.8

Table 3. Performance comparison for 51 Peg.

The **convergence time** for DNS was **huge.**

Solutions are both more accurate and precise for APT.

The **evidence** has **better constraints** with DNS. But since **convergence is slow**, we need to constrain the search boundaries, rendering the evidence (which is prior volume-dependent) nuanced by them. Bringing forth the question:

what good is the evidence then, for model comparison?

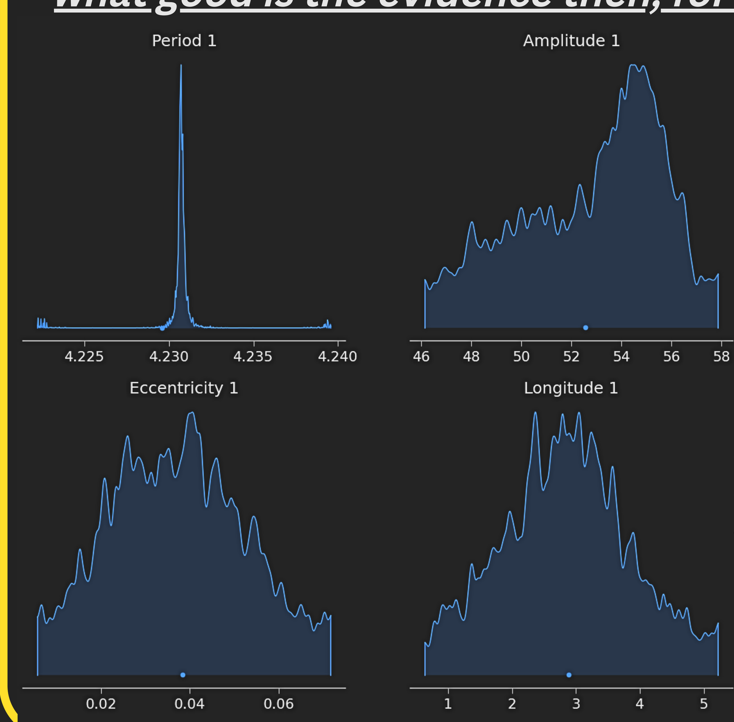


Fig 4. 94% High Density Intervals for the keplerian block. The dot indicates the mean.

EPISODE III
REVENGE OF THE MCMC

EMPEROR's default sampler is **reddemcee,** which is an original **Adaptative Parallel Tempering** implementation of the *emcee* sampler. **APT** is characterised for it's speed and robustness.

- Each **replica** is annealed by a factor $\beta \in [0, 1]$
- Hotter systems have **local maximas closer to each other**
- Sampling is **less likely to get stuck in local maxima**
- **Replica exchange** between systems
- β **ladder adapts** as a function of replica acceptance rate
- Evidence estimated with **thermodynamic integration**

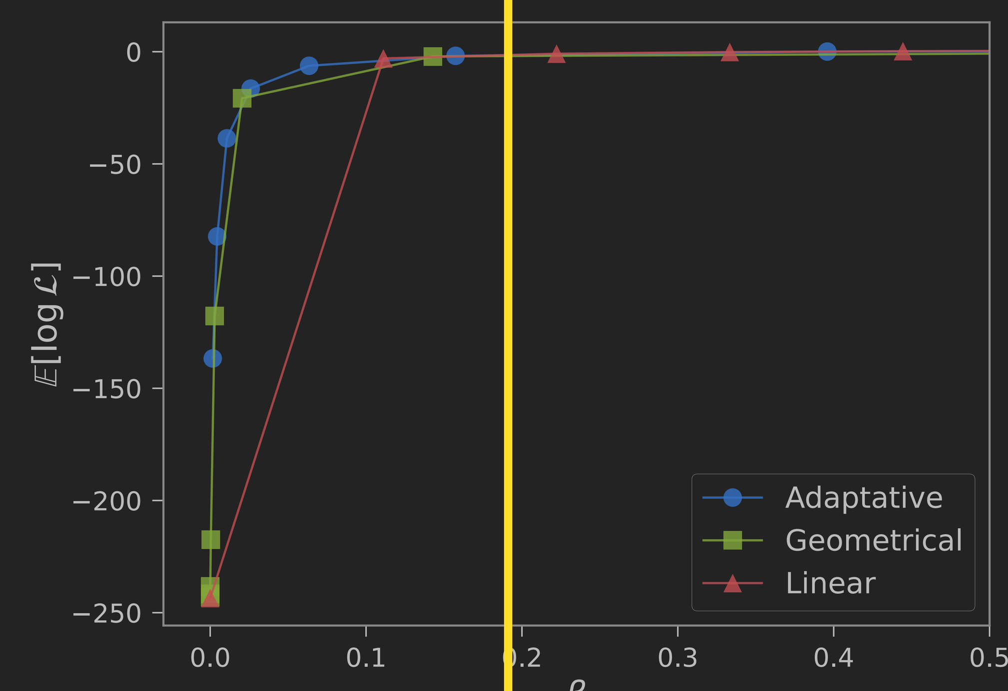


Fig 1. Different temperature ladder schemes for the thermodynamic integration.

$$\Delta \log(Z) \equiv \int_0^1 \mathbb{E}[\log \mathcal{L}]_\beta d\beta$$

Thermodynamic Integration uses the ergodicity of the chain to express the evidence in terms of the mean log likelihood.

EPISODE VI
WHAT I HOPE...

APT seems exceptionally **better suited for wide searches**, in both **speed and performance**.

Let's take a look at this '*mystery system*', for complexity's sake:

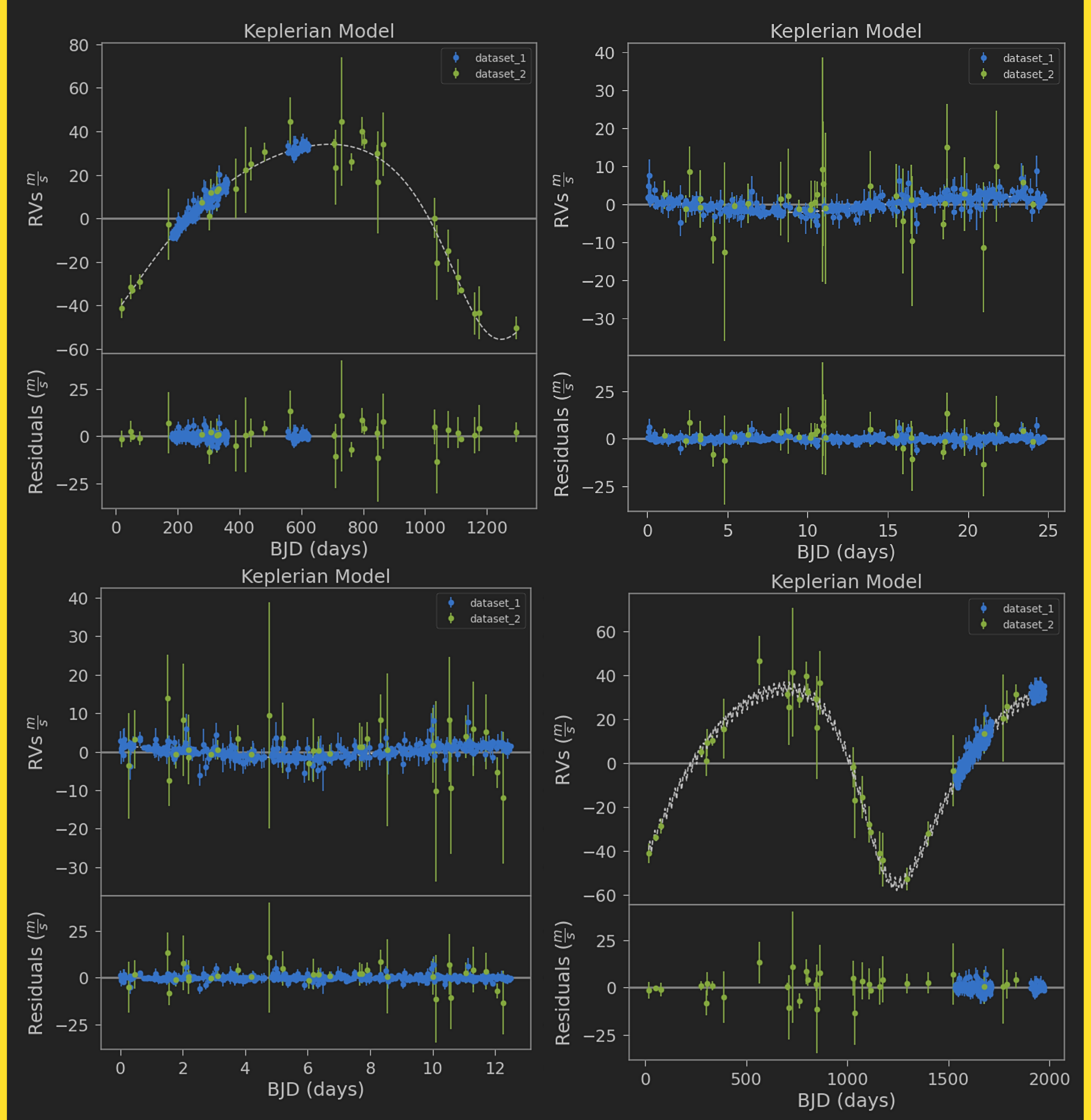


Fig 5. 3 signals, 2 instruments.
P = [1352, 24.8, 12.5] days. K = [44.8, 2.1, 1.5] ms-1

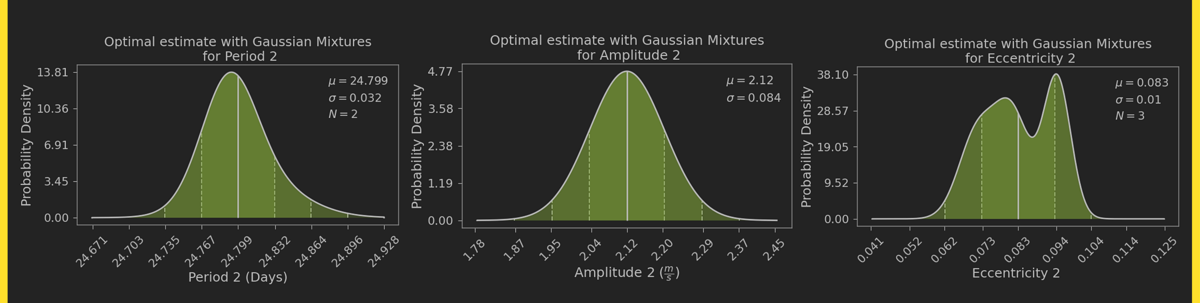


Fig 6. BGM posterior estimation for the second Keplerian block.

...TO DO IN THE FUTURE

EMPEROR has evolved greatly since it's first version and has been used in 7 published works already.

At this moment, leading the to-do list:

- Submit paper
- Merge with EMPEROR's photometry version
- Add astrometry models
- Include beta ladder schemes, ie. Feedback Optimised
- MOM estimates for Keplerian priors

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