Applications of Bayesian Framework to optimal observational design strategies. The case of ESPRESSO follow-up of TESS targets

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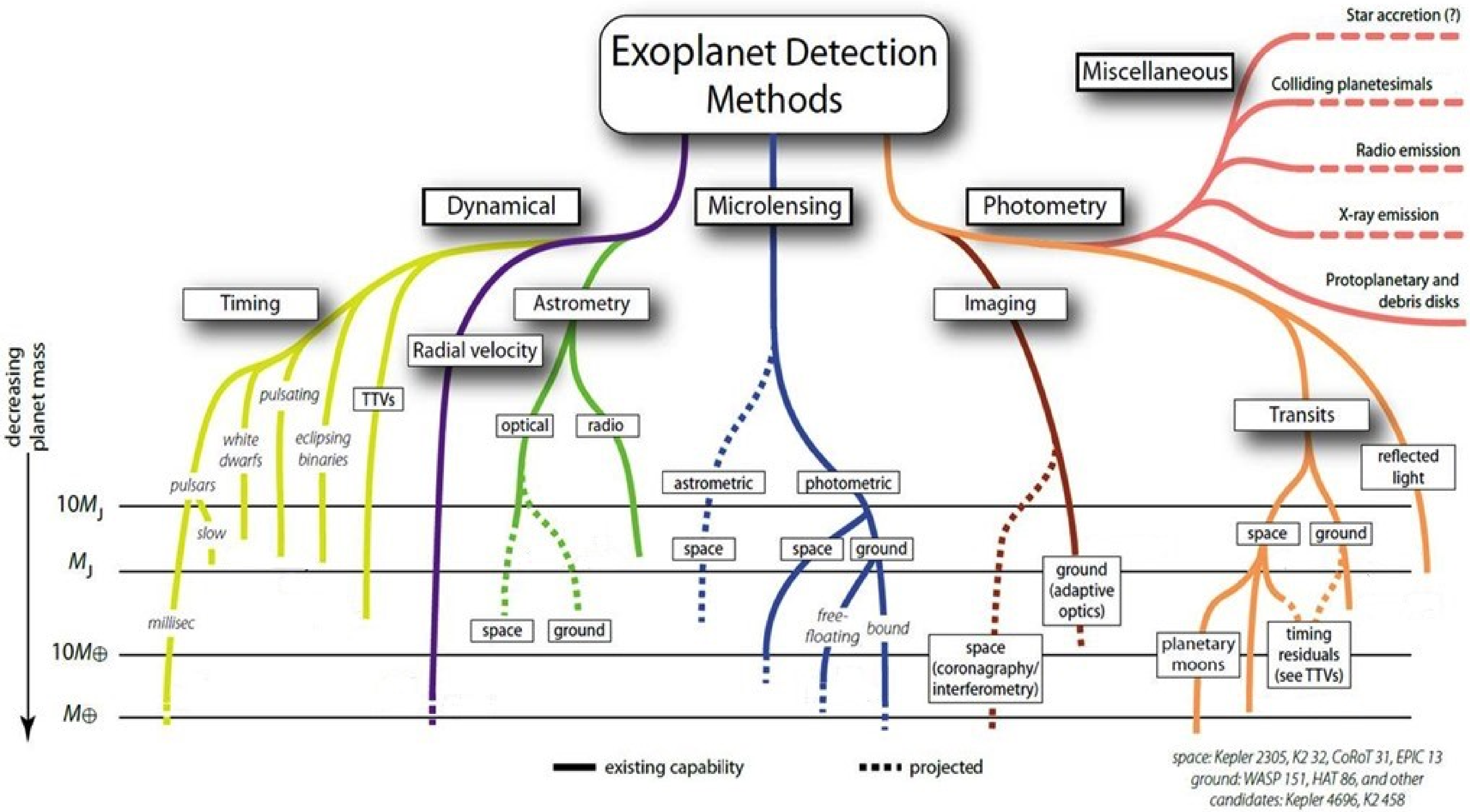
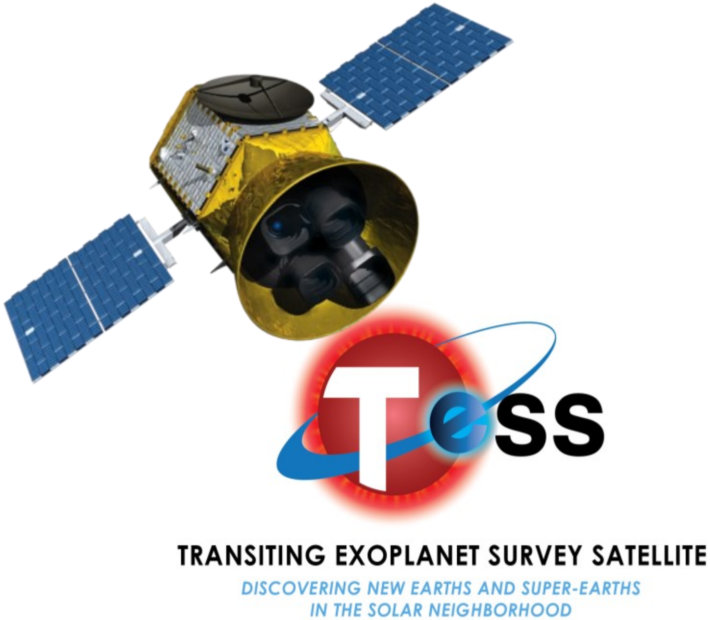
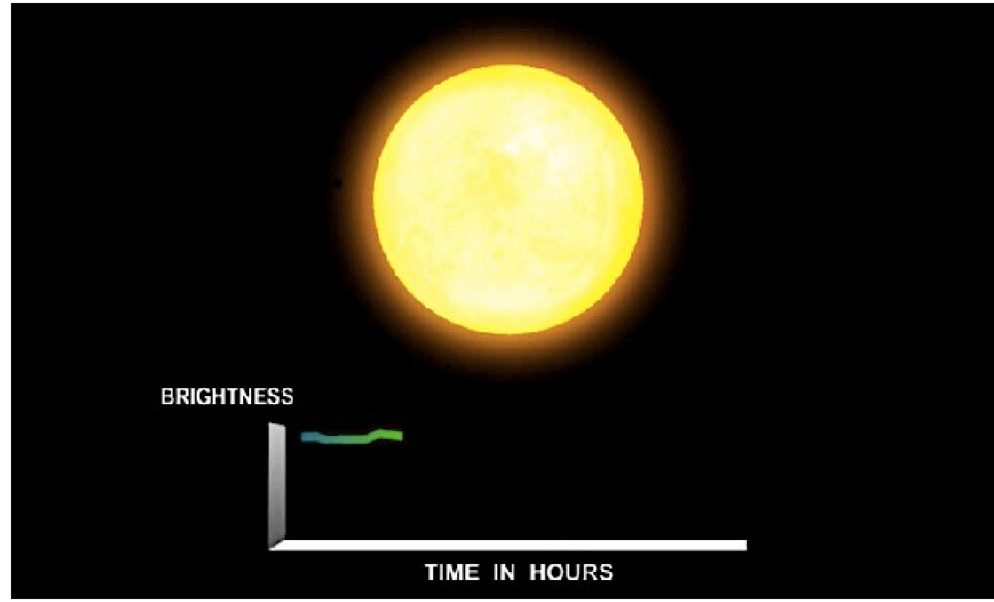
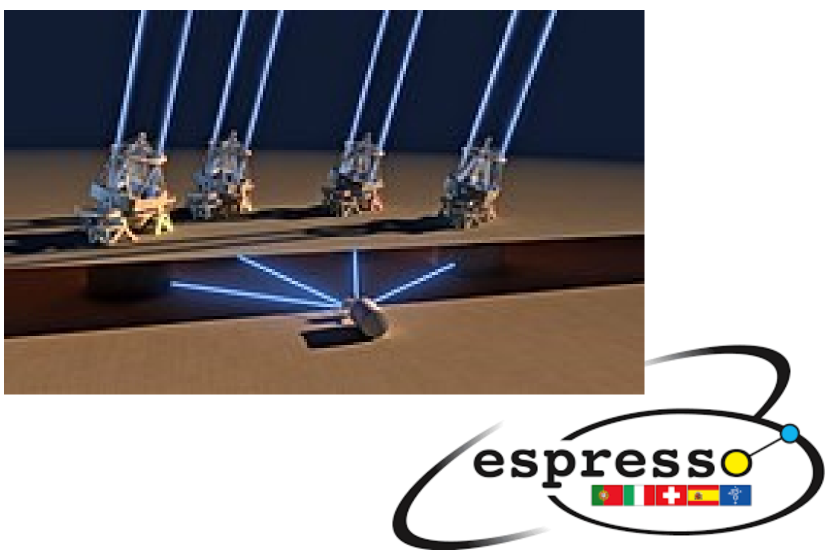
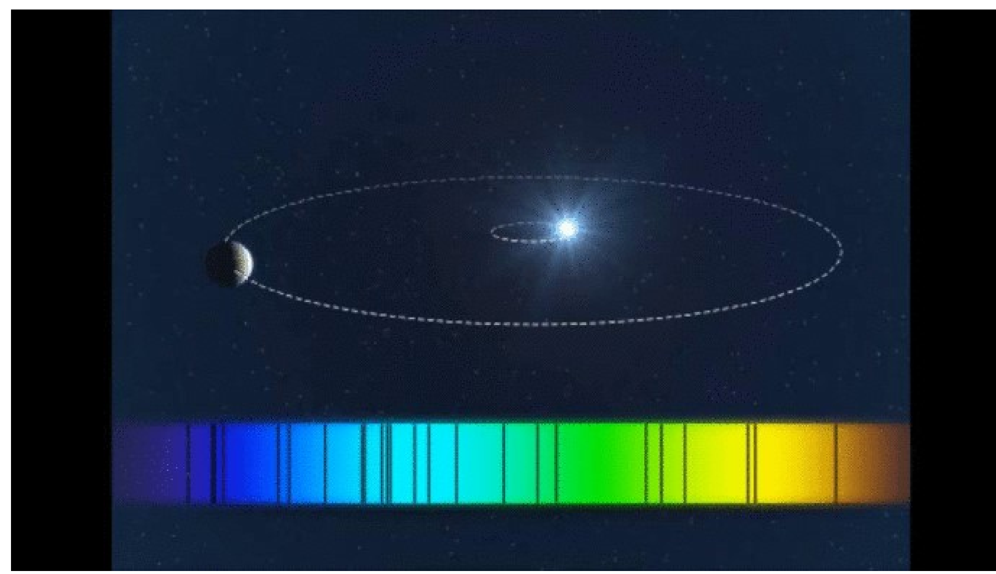


On the 10th of September there were 4333 confirmed exoplanets in 3201 systems, with 709 multiple planet systems according to exoplanet.eu


TESS
TRANSITING EXOPLANET SURVEY SATELLITE
DISCOVERING NEW EARTHS AND SUPER-EARTHS
IN THE SOLAR NEIGHBORHOOD

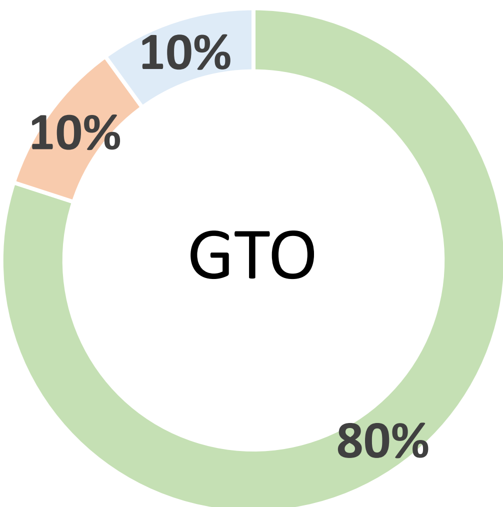

BRIGHTNESS
TIME IN HOURS

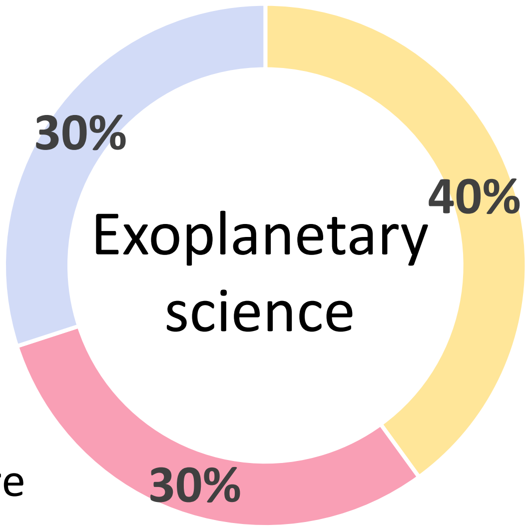

espresso



ESPRESSO GTO

273 nights in 4 years

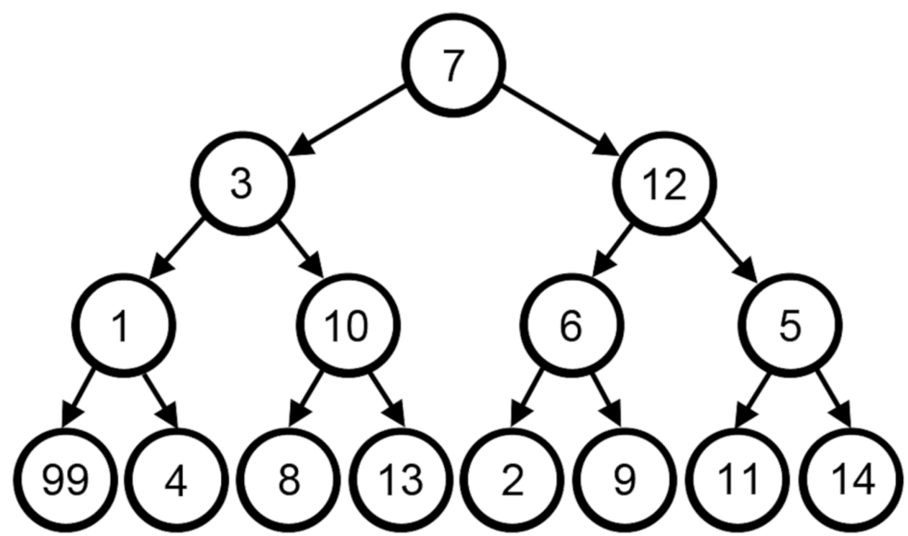




Local optimization the greedy algorithm

A convenient entry point into optimization scheduling can be provided through a "Greedy" algorithm.

However, it is well known that local optimizers such as the greedy algorithm cannot provide global optimization.



Local optimization the greedy algorithm

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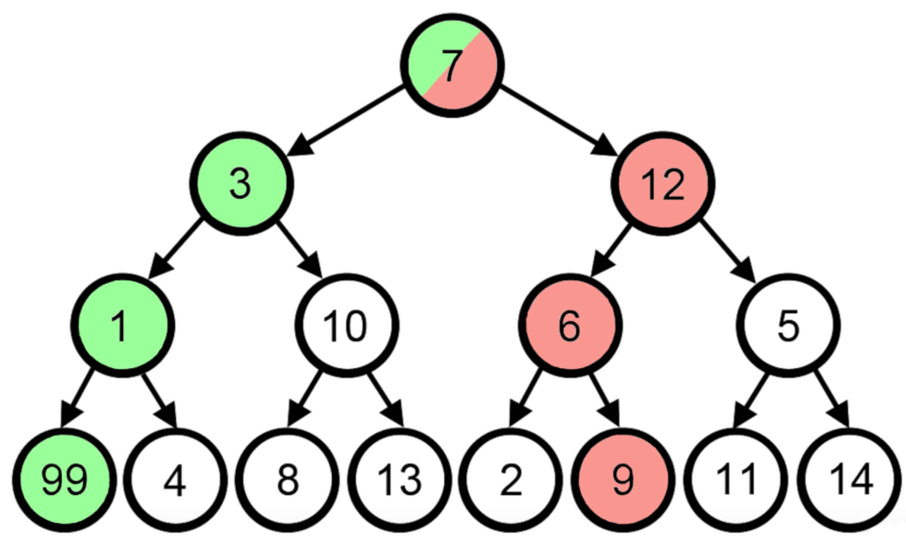
However, it is well known that local optimizers such as the greedy algorithm cannot provide global optimization.

Greedy algorithms can fail to find the globally optimal solution because they do not consider all the data.



The utility function in the Bayesian approach

The utility function U involved in Bayesian optimal design measures the benefit of taking a particular action given the possible outcomes.

$$EU(a) = \sum_{o} p(o, I_a) U(a, o)$$

where I_a represents the prior information about the possible outcomes.

The best action $\hat{a}$, is the one that maximizes the expected utility

$$\hat{a} = \operatorname{argmax}_a EU(a)$$

Optimal design

We denote with e the experiment and with D_e the values of future data from the experiment.

Finding the optimal experimental design requires the specification of an utility $U(D_e|e)$.

Once the utility is specified, the best experiment is the one that maximizes:

$$\mathbb{E}U(e) = \int P(D_e|D_c, e)U(D_e|e)dD_e$$

Myopic vs non myopic strategy

I concentrated my interest on those algorithms whose objective function leads to a sampling of the RV phase-curves of the known transiting planets as uniform as possible. *Burt et al. [2018]*

The objective in this work is to quantify the difference in efficiency, with respect to the information gained about exoplanet masses and orbital parameters through RV measurements, between myopic and non-myopic scheduling algorithms.

I simulated the scheduling of ESPRESSO GTO observations from the 1^{th} of October 2019 until the 30^{th} of September 2022 and I draw 10 different distributions for the ESPRESSO GTO with 1102 slots for TOI follow-up

Scheduling strategies

I compared three different scheduling strategies

- A1 completely random
  with airmass <2 and >30° from the Moon

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- A1 completely random

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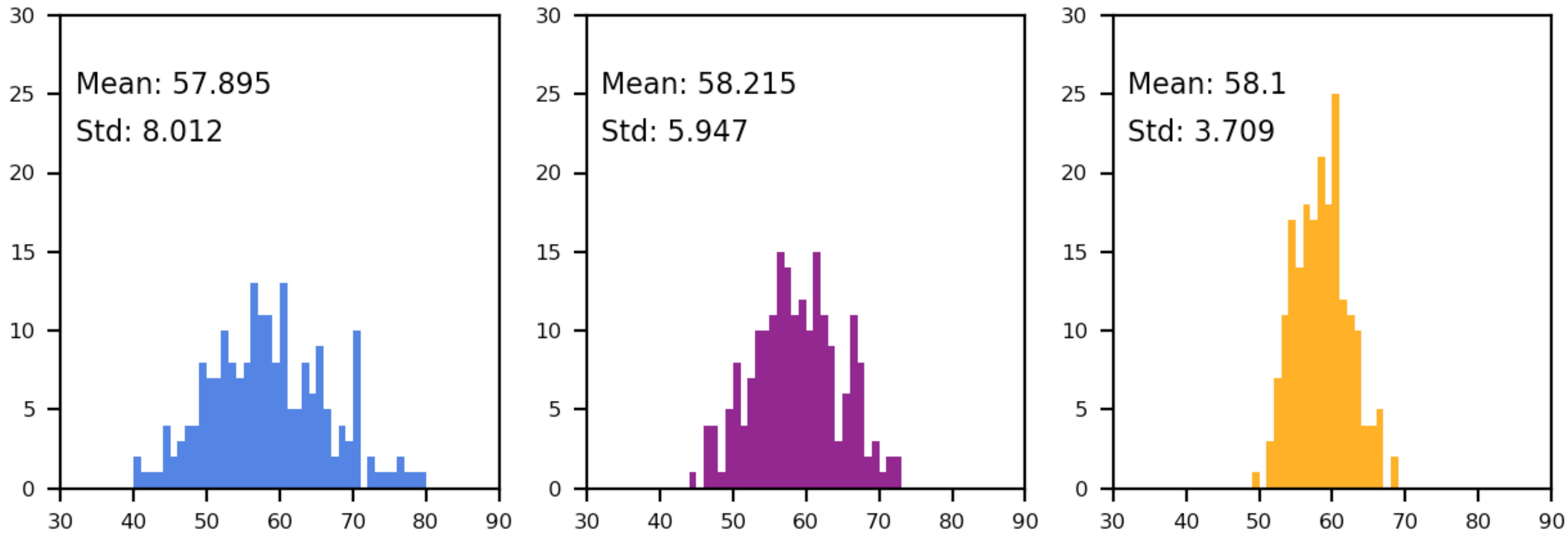
- A2 with the same constraints of A1 but the target must maximize the objective function

$$f(\{x_i\}) \equiv \left\{ \sum_{i=1}^{1102} [d(x_i)]^{-2} \right\}^{-\frac{1}{2}}$$

Where $d(x_i)$ is the time distance between x_i observation and its nearest neighbour

Scheduling strategies

- The B strategy, is non-myopic. In this case, the aim is to compare all possible schedules, across the full time-span of 3 years, and then choose that which maximizes the same objective function of the A2 design.



Histograms of the number of RV observations per bin, for the three scheduling strategies, A1 (left panel), A2 (central panel) and B (right panel).

Results for transiting planets

- absolute bias, $\mathbf{E}[X] - X_{true}$
- relative bias, $(\mathbf{E}[X] - X_{true})/X_{true}$
- absolute accuracy, $| \mathbf{E}[X] - X_{true} |$
- relative accuracy, $| \mathbf{E}[X] - X_{true} | /X_{true}$
- absolute precision, σ_X
- relative precision, $\sigma_X/\mathbf{E}[X]$

Where X_{true}, $\mathbf{E}[X]$ and σ_X represent, respectively, the true , the expected and standard deviation of X

Strategy	Parameter	Absolute			Relative		
		Bias	Accuracy	Precision	Bias	Accuracy	Precision
A_1	K	0.25 ± 0.36	0.52 ± 0.32	0.90 ± 0.54	0.12 ± 0.21	0.21 ± 0.20	0.31 ± 0.21
	e	0.10 ± 0.08	0.11 ± 0.06	0.11 ± 0.05	14.39 ± 44.04	14.46 ± 44.01	0.70 ± 0.10
	M	0.40 ± 0.90	1.43 ± 0.85	2.27 ± 1.59	0.07 ± 0.17	0.19 ± 0.17	0.27 ± 0.15
A_2	K	0.11 ± 0.21	0.44 ± 0.18	0.63 ± 0.21	0.06 ± 0.15	0.18 ± 0.14	0.26 ± 0.21
	e	0.08 ± 0.08	0.10 ± 0.06	0.10 ± 0.04	14.71 ± 46.15	14.80 ± 46.512	0.70 ± 0.10
	M	0.08 ± 0.63	1.26 ± 0.64	1.67 ± 0.67	0.03 ± 0.12	0.17 ± 0.12	0.23 ± 0.14
B	K	0.05 ± 0.19	0.39 ± 0.13	0.58 ± 0.19	0.05 ± 0.14	0.16 ± 0.13	0.25 ± 0.20
	e	0.08 ± 0.07	0.09 ± 0.06	0.10 ± 0.04	13.64 ± 39.94	13.48 ± 39.92	0.69 ± 0.11
	M	−0.05 ± 0.55	1.15 ± 0.50	1.56 ± 0.61	0.01 ± 0.11	0.15 ± 0.11	0.22 ± 0.14

Results for non transiting planets

- absolute bias, $\mathbf{E}[X] - X_{true}$
- relative bias, $(\mathbf{E}[X] - X_{true})/X_{true}$
- absolute accuracy, $|\ \mathbf{E}[X] - X_{true}\ |$
- relative accuracy, $|\ \mathbf{E}[X] - X_{true}\ |\ /X_{true}$
- absolute precision, σ_X
- relative precision, $\sigma_X/\mathbf{E}[X]$

Where X_{true}, $\mathbf{E}[X]$ and σ_X represent, respectively, the true , the expected and standard deviation of X

Strategy	Parameter	Absolute			Relative		
		Bias	Accuracy	Precision	Bias	Accuracy	Precision
A_1	K	−8.56 ± 25.04	11.97 ± 23.64	10.04 ± 11.64	−0.01 ± 0.28	0.19 ± 0.22	0.24 ± 0.15
	e	0.04 ± 0.06	0.05 ± 0.05	0.09 ± 0.05	3.32 ± 5.62	3.41 ± 5.57	0.87 ± 0.30
	P	56.87 ± 568.78	352.88 ± 451.90	626.04 ± 467.78	0.15 ± 0.37	0.26 ± 0.31	0.78 ± 1.07
	M	−180.26 ± 654.75	306.02 ± 606.78	257.13 ± 356.90	0.01 ± 0.35	10.04 ± 20.02	0.32 ± 0.19
A_2	K	−5.96 ± 21.12	9.32 ± 19.87	8.08 ± 9.88	0.24 ± 0.67	0.38 ± 0.60	0.28 ± 0.23
	e	0.04 ± 0.07	0.06 ± 0.06	0.08 ± 0.05	2.79 ± 4.44	2.91 ± 4.37	0.87 ± 0.34
	P	257.82 ± 729.02	481.58 ± 605.37	701.87 ± 722.12	0.20 ± 0.37	0.28 ± 0.31	0.88 ± 2.24
	M	−128.34 ± 556.24	244.17 ± 516.14	214.77 ± 324.32	0.32 ± 0.84	22.29 ± 39.88	0.36 ± 0.26
B	K	−6.27 ± 21.98	10.03 ± 20.55	8.50 ± 10.39	0.19 ± 0.55	0.35 ± 0.46	0.26 ± 0.20
	e	0.05 ± 0.06	0.06 ± 0.05	0.08 ± 0.05	3.39 ± 5.37	3.48 ± 5.31	0.87 ± 0.36
	P	268.97 ± 853.49	518.99 ± 731.88	759.89 ± 702.79	0.22 ± 0.44	0.31 ± 0.37	1.04 ± 1.99
	M	−137.18 ± 584.83	263.35 ± 540.07	220.32 ± 346.71	0.27 ± 0.73	23.90 ± 48.20	0.34 ± 0.22

Results

The myopic strategies lead to a biased estimation, of the order of 5% of the mass of the simulated TOIs

In contrast, the non-myopic strategy is able to provide an unbiased (<1%) measurement of the masses.

All the strategies are able to find the same number of non-transiting planets.

Cabona et al. [2020] *arXiv preprint:2005.14008*

THANK YOU

FOR

WATCHING

MY SLIDESHOW