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DISCOVERY AND CHARACTERISATION OF EXTRASOLAR PLANETS

boosted by machine learning algorithms

Rodrigo F. Díaz

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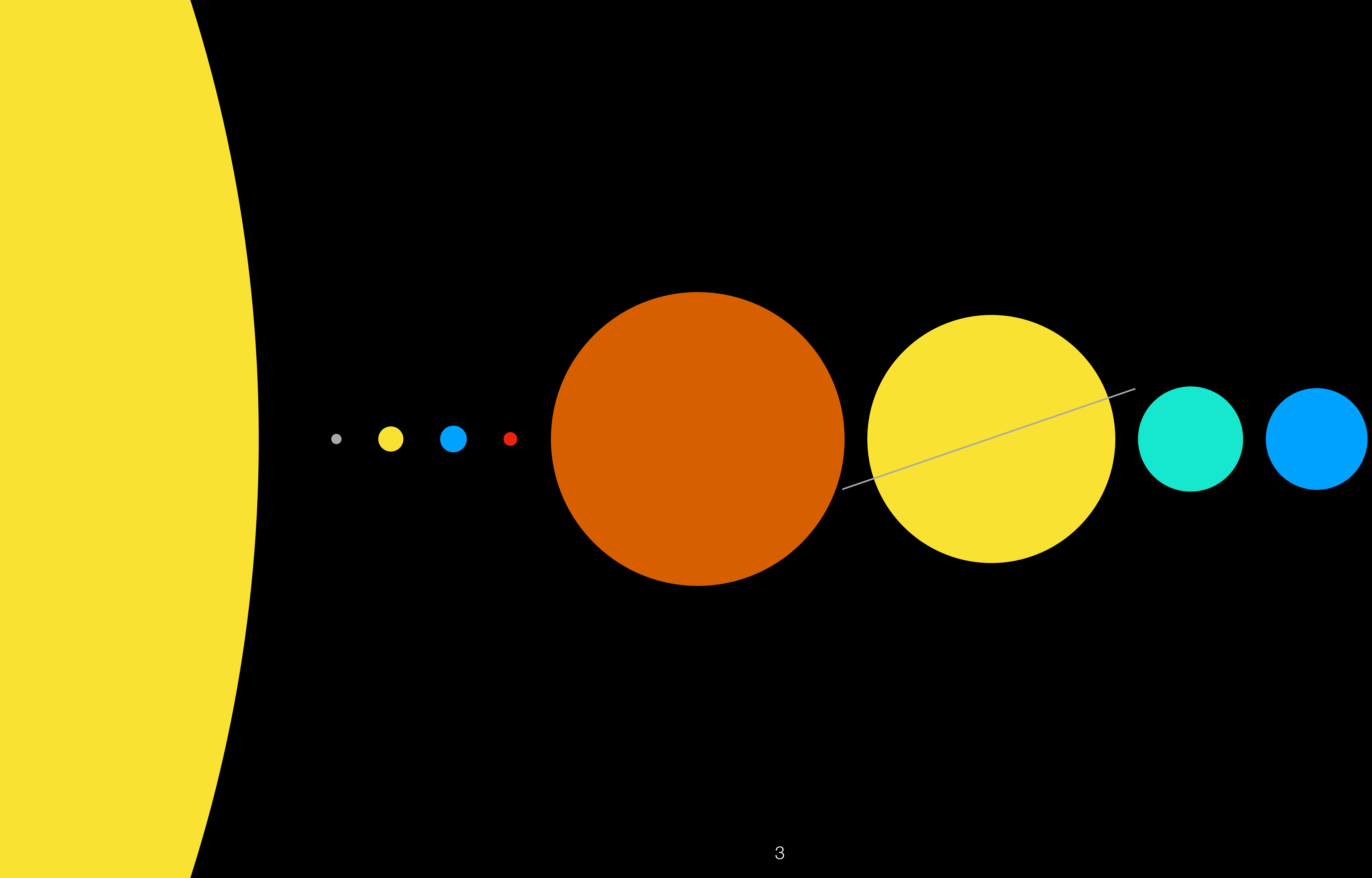
@RDextrasolar

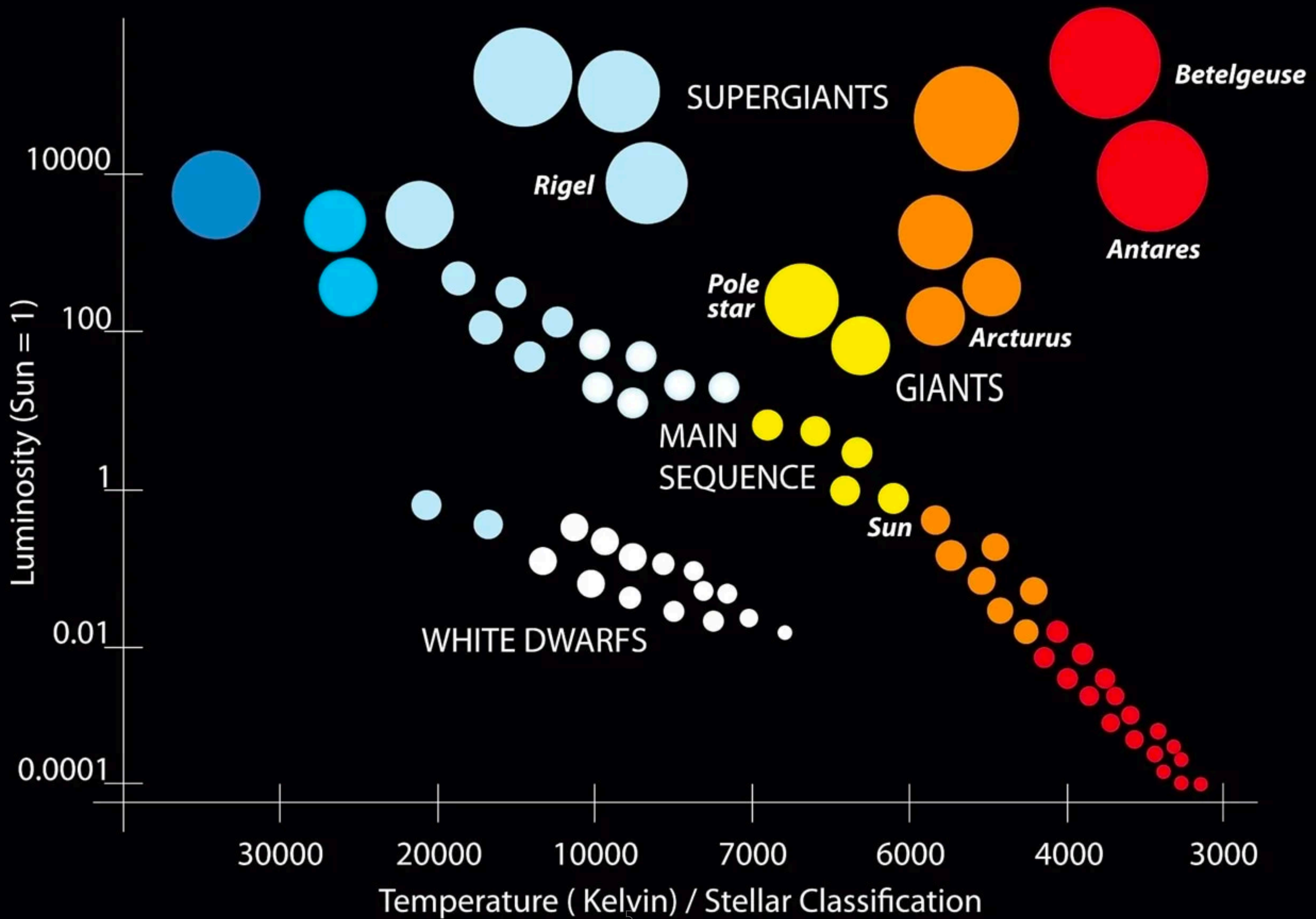
ICAS

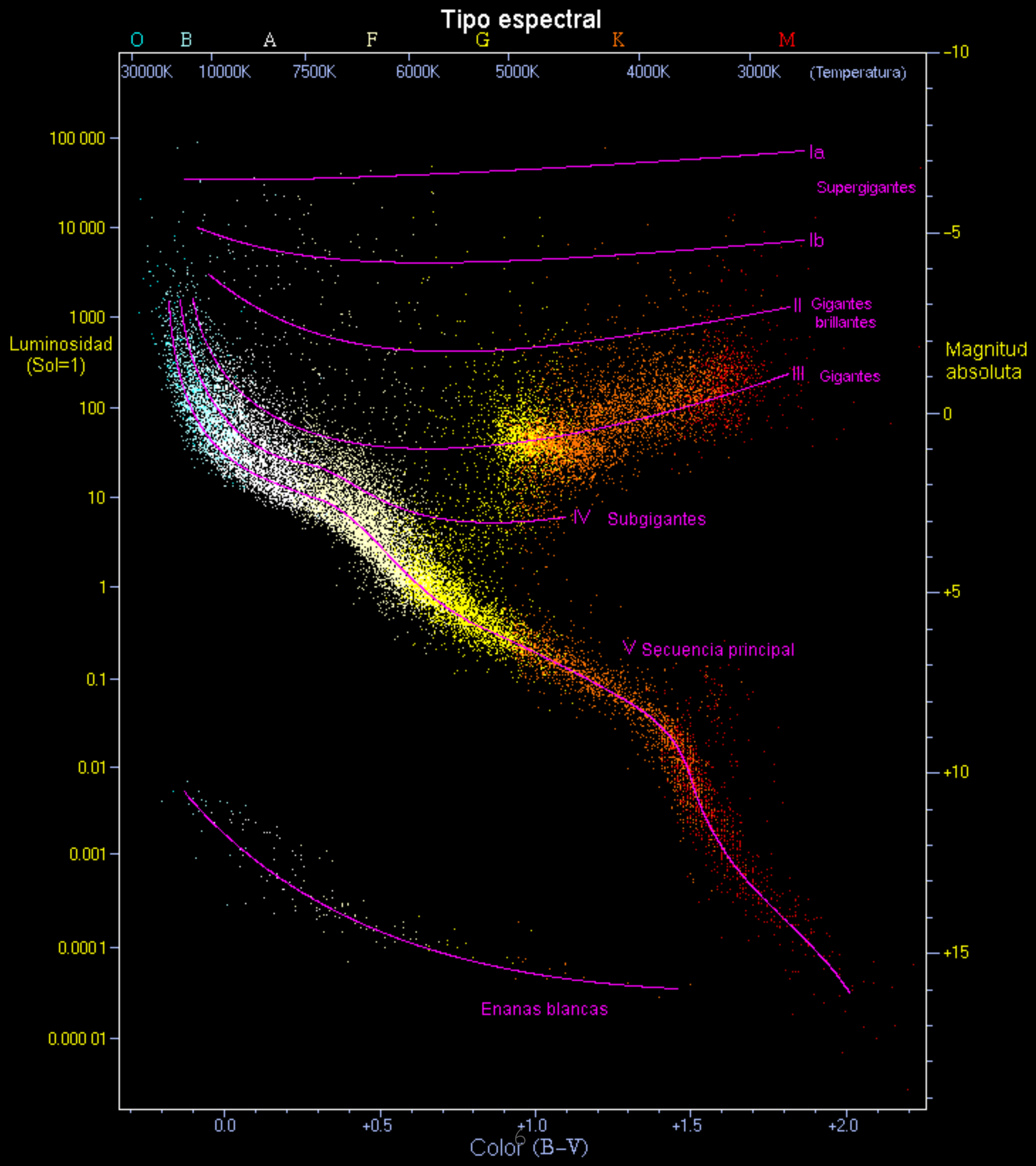
OUTLINE

- Overview of exoplanets
- Current limitations
- Our contribution using machine learning
- Bonus track: the advent of JWST




Jupiter
5 AU
P ~ 12 yr
1 Mj = 1.9e27 kg ~ 318 Mt
1 Rj = 69 911 km ~ 11 Rt
Mercury
0,39 AU
P = 88 d
Mm ~ Mt/18
Rm ~ Rt/2.6
Earth
1 AU
P = 365,25 d
1 Mt = 5,9e24 kg
1 Rt = 6371 km
Neptune
30 AU
P ~ 165 yr
1 Mn ~ 17 Mt
1 Rn ~ 3,8 Rt
Sun
1 Ms = 1.988e30 kg ~ 1000 Mj
1 Rs = 695 700 km ~ 10 Rj


SUPERGIANTS
Betelgeuse
Rigel
Antares
Pole star
Arcturus
GIANTS
MAIN SEQUENCE
Sun
WHITE DWARFS
10000
100
1
0.01
0.0001
Luminosity (Sun = 1)
30000
20000
10000
7000
6000
4000
3000
Temperature (Kelvin) / Stellar Classification


Tipo espectral
O
B
A
F
G
K
M
30000K
10000K
7500K
6000K
5000K
4000K
3000K
(Temperatura)
100 000
10 000
1000
100
10
1
0.1
0.01
0.001
0.0001
0.000 01
Luminosidad
(Sol=1)
-10
-5
0
+5
+10
+15
Magnitud
absoluta
Ia
Supergigantes
Ib
II Gigantes
brillantes
III Gigantes
IV Subgigantes
V Secuencia principal
Enanas blancas
0.0
+0.5
+1.0
+1.5
+2.0
Color (B–V)

Some questions

What kind of planets are possible?

How common are planetary systems?

How common is the Solar System? And Earth?

What are planets made of?

What are there atmospheres like?

What can we learn about their formation and evolution by studying the architecture of systems?

How do formation and evolution depend on stellar parameters?

…

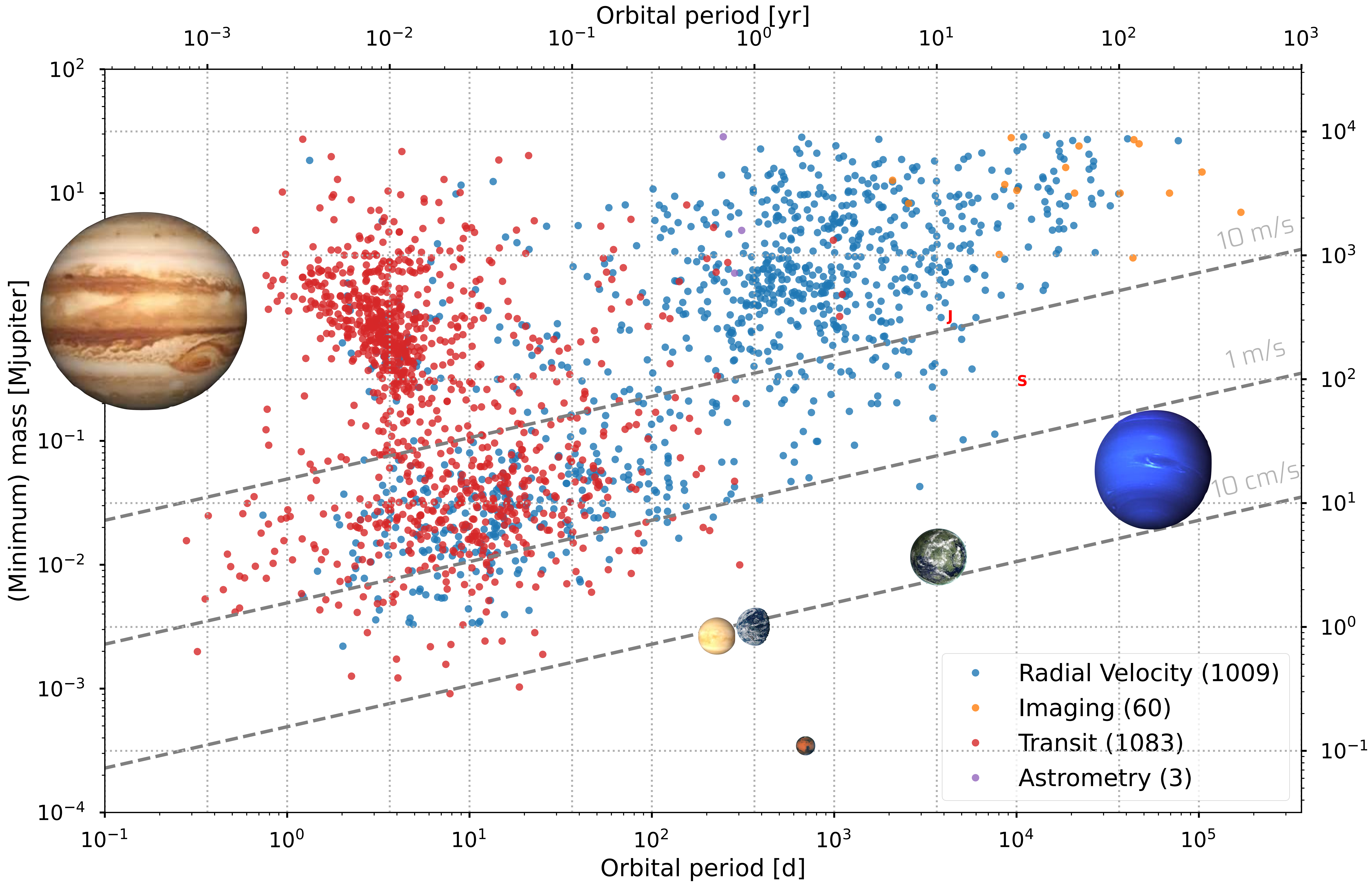
Are we alone?

G.Hüdepohl (atacamaphoto.com)/ESO

5539

known exoplanets

according to NASA Exoplanet Archive (on April 25 2021)

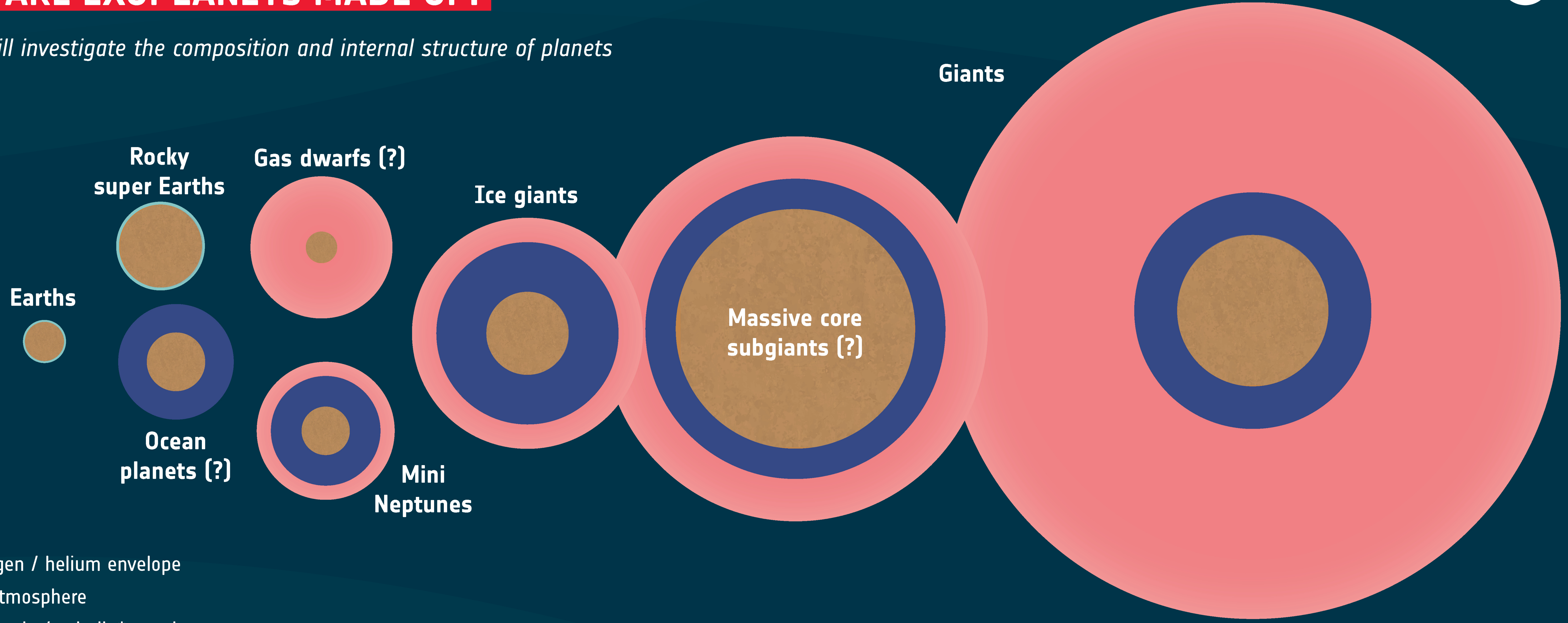


Orbital period [yr]
Orbital period [d]
(Minimum) mass [Mjupiter]
(Minimum) mass [Mearth]
10 m/s
1 m/s
10 cm/s
J
S
Radial Velocity (1009)
Imaging (60)
Transit (1083)
Astrometry (3)

DIVERSE INTERNAL STRUCTURE

➔ WHAT ARE EXOPLANETS MADE OF?

How Cheops will investigate the composition and internal structure of planets

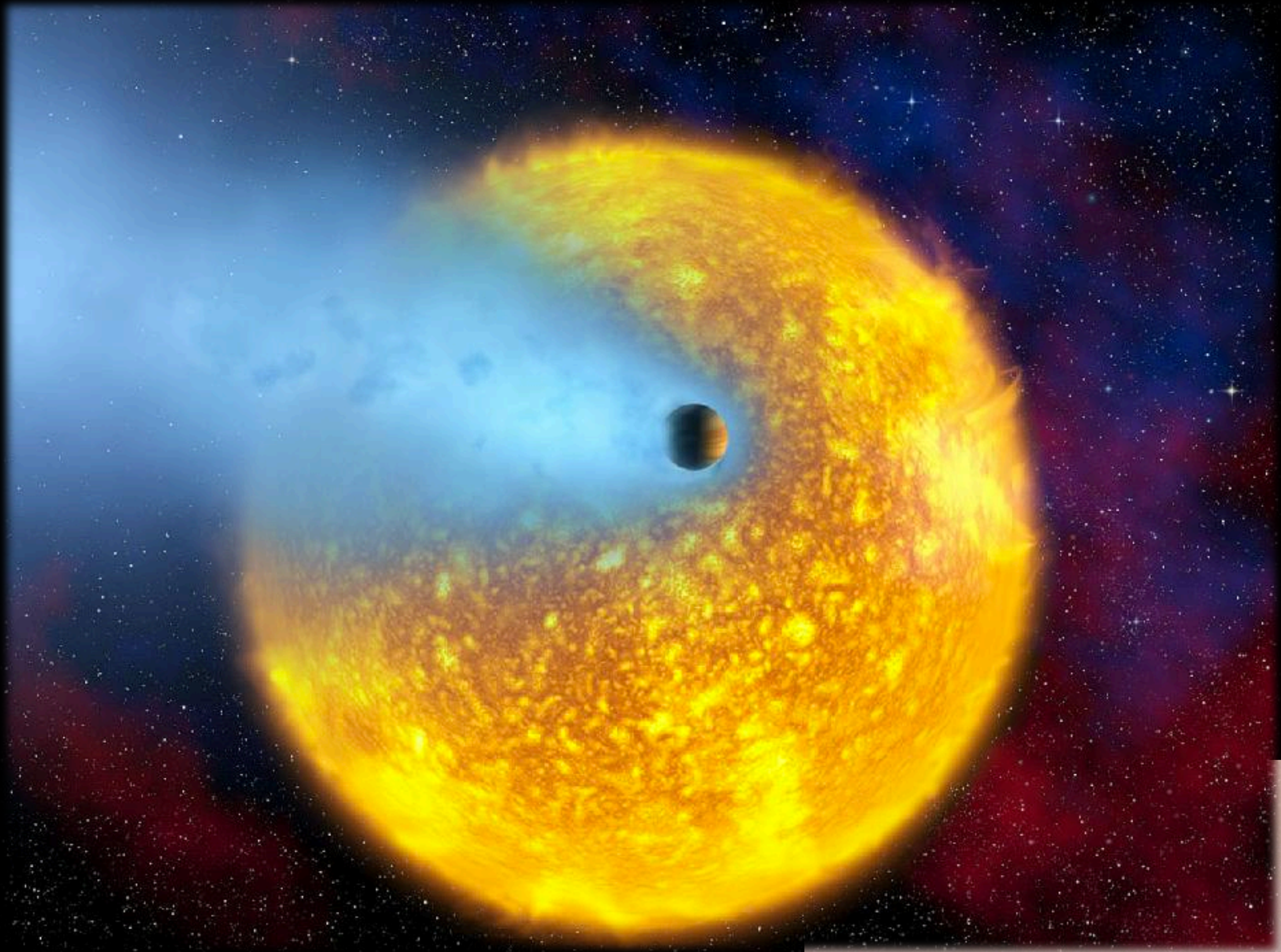


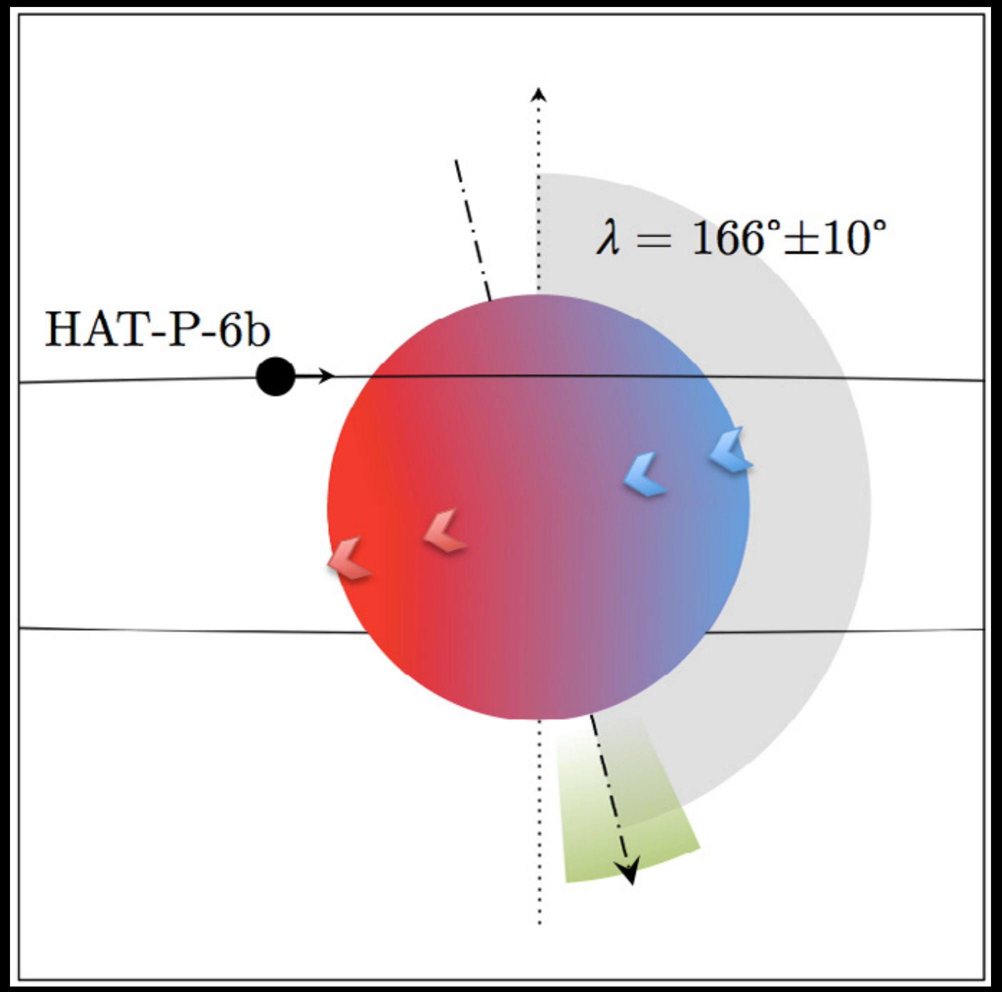
- Hydrogen / helium envelope
- Thin atmosphere
- Ice mantle / volatile* envelope
- Solid core (rocks, metals)

* *Planetary scientists call* ***volatiles*** *all chemical elements and compounds with low boiling points that are associated with a planet's or moon's crust or atmosphere. These include: nitrogen, water, carbon dioxide, ammonia, hydrogen, methane and sulphur dioxide.*

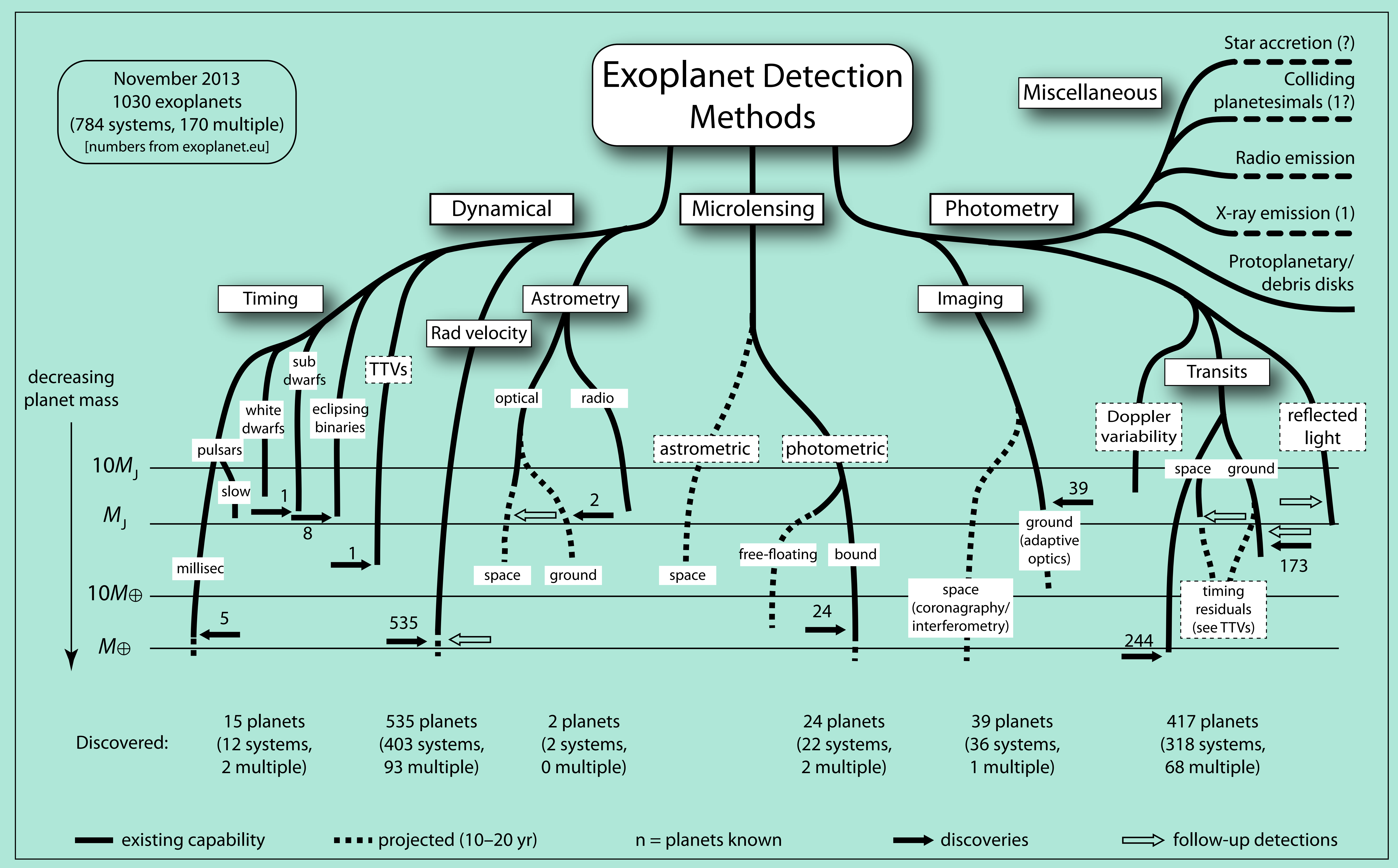
Super Earths | Neptunes | Jupiters

1 M_{Earth} | 10 M_{Earth} | 100 M_{Earth} | 300 M_{Earth} ~ 1 $M_{Jupiter}$ | 1000 M_{Earth} | (M=mass)



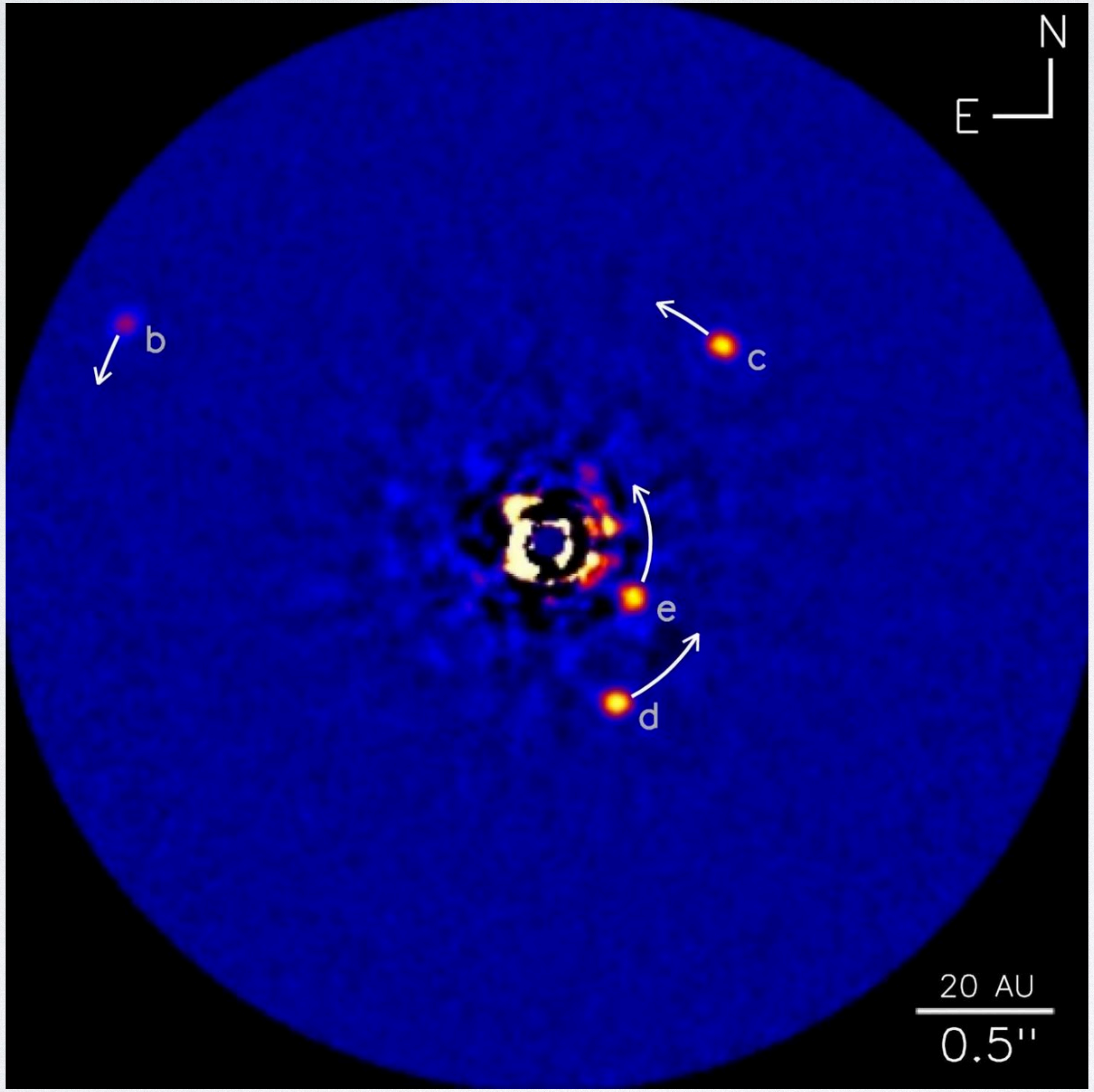


Hébrard, Ehrenreich, Bouchy, et al. (2011)



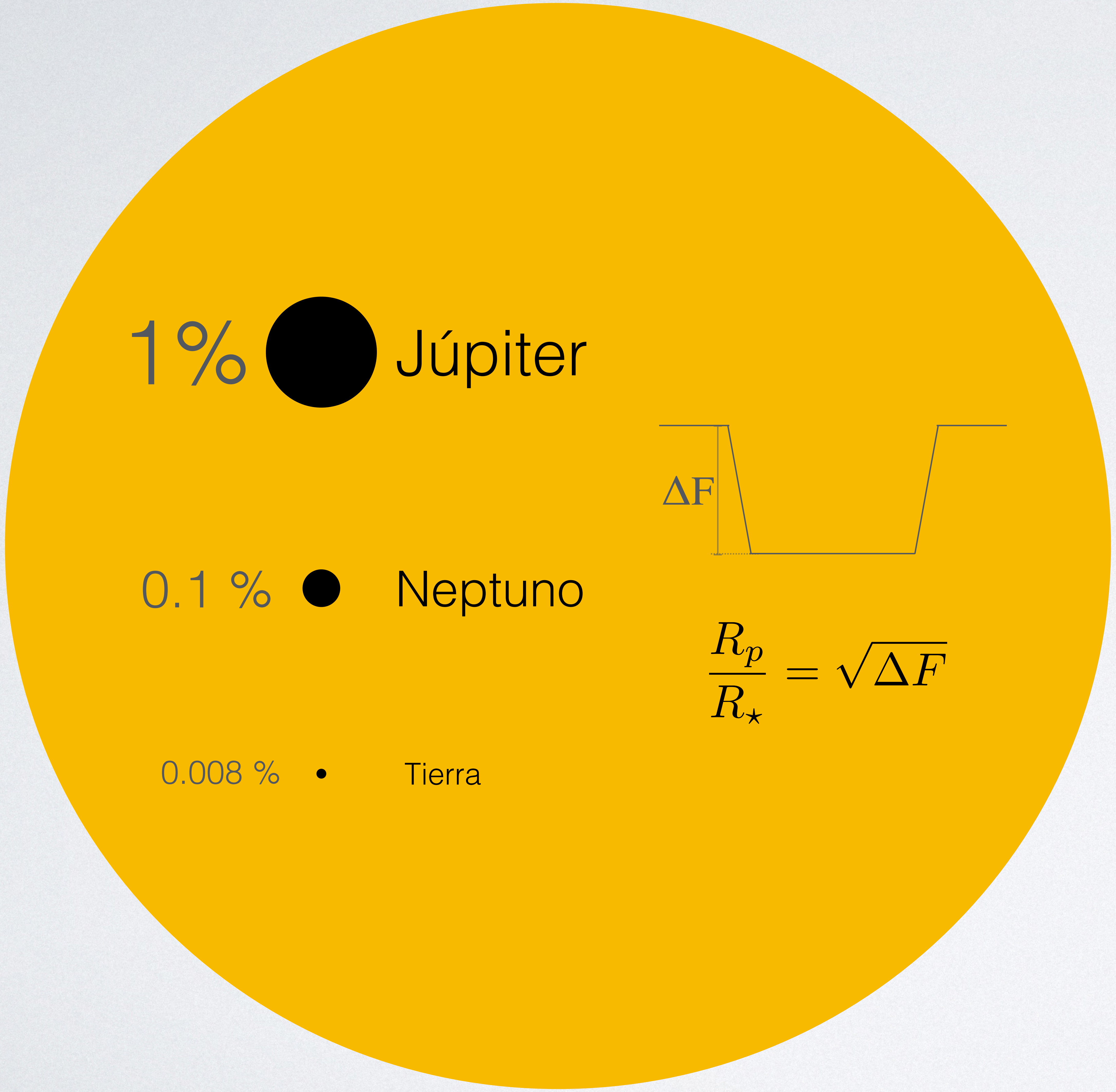
Perryman (2013)

DIRECT IMAGING



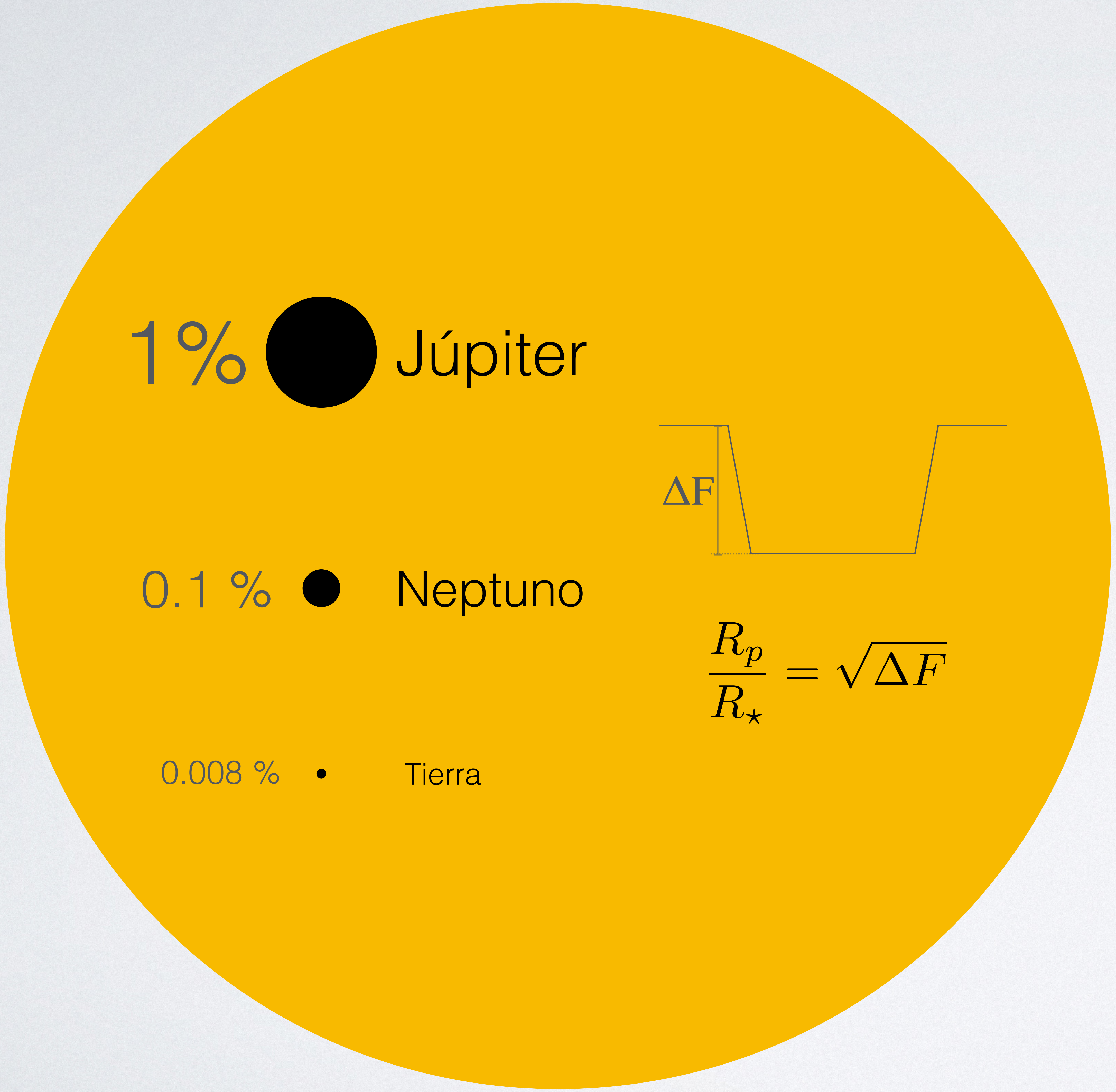
$$\frac{f_\oplus}{f_\odot} = 10^{-10}$$

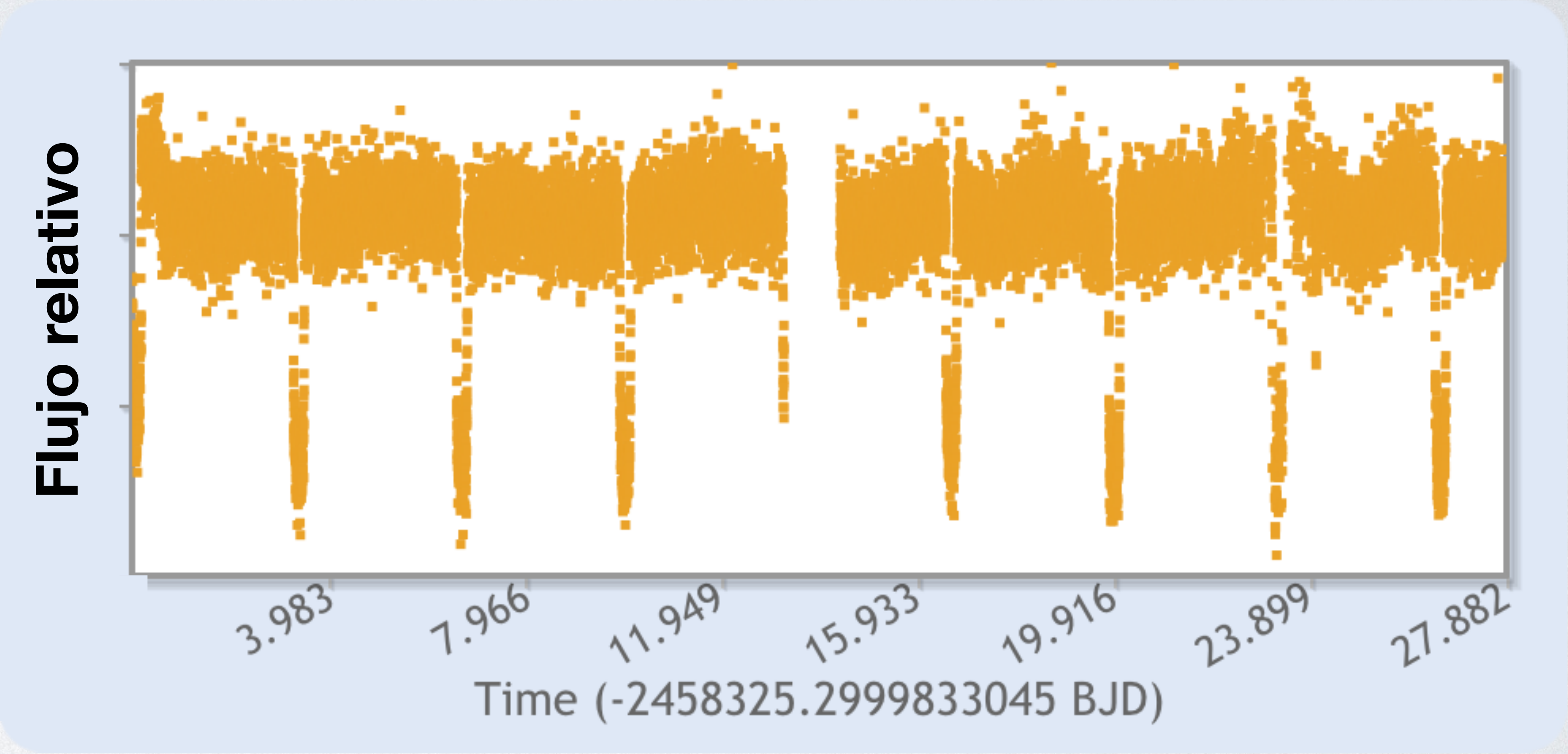
TRANSIT METHOD

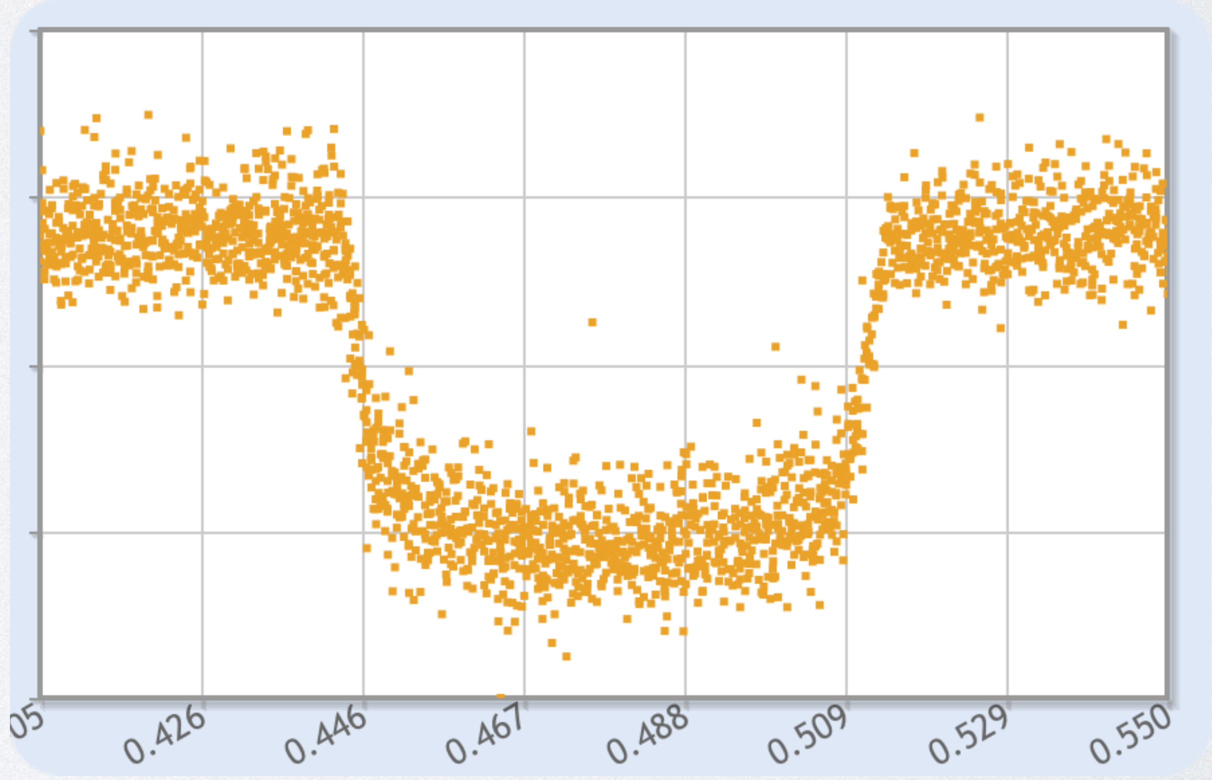


$$\frac{R_p}{R_\star} = \sqrt{\Delta F}$$

TRANSIT METHOD







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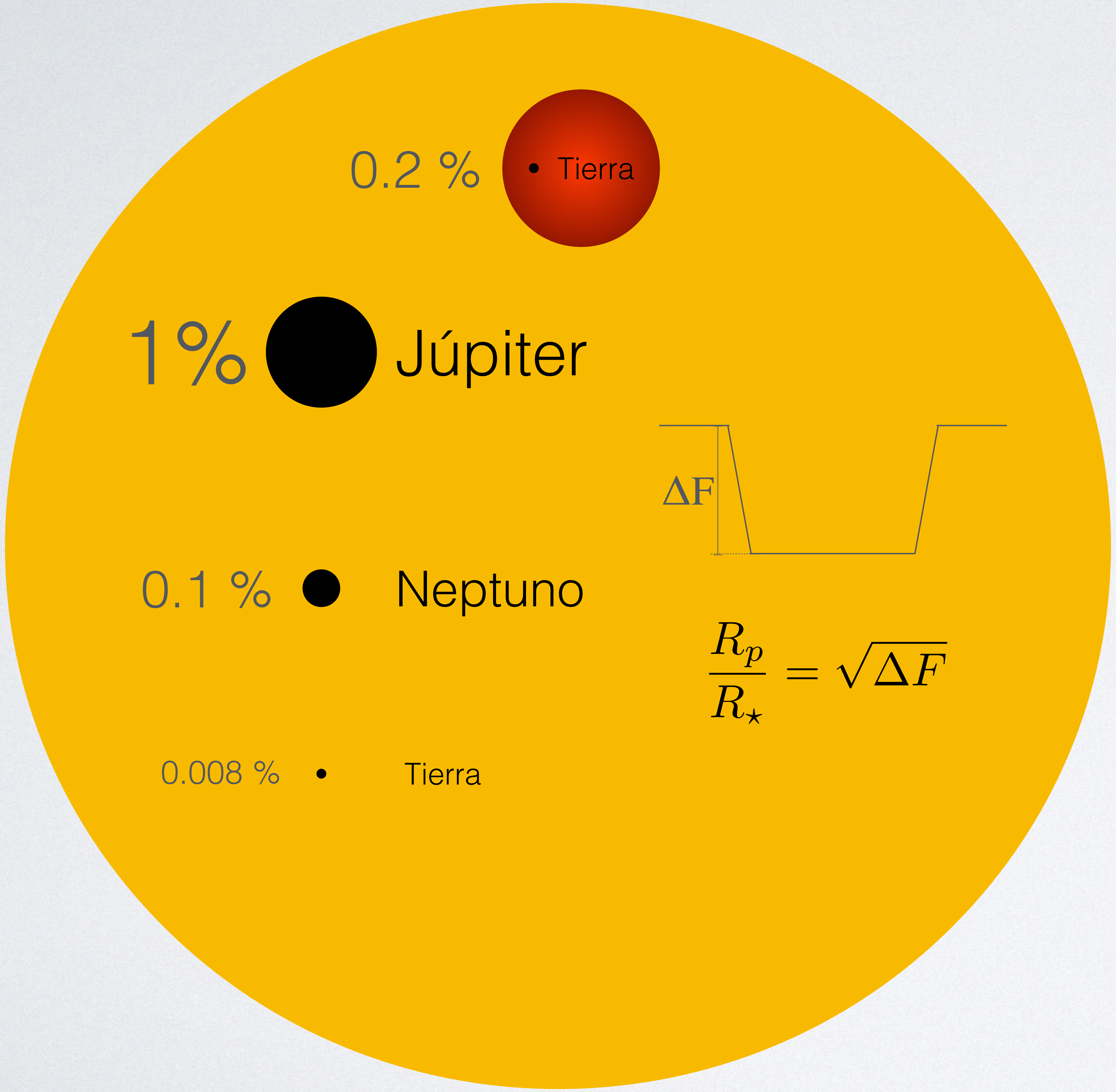

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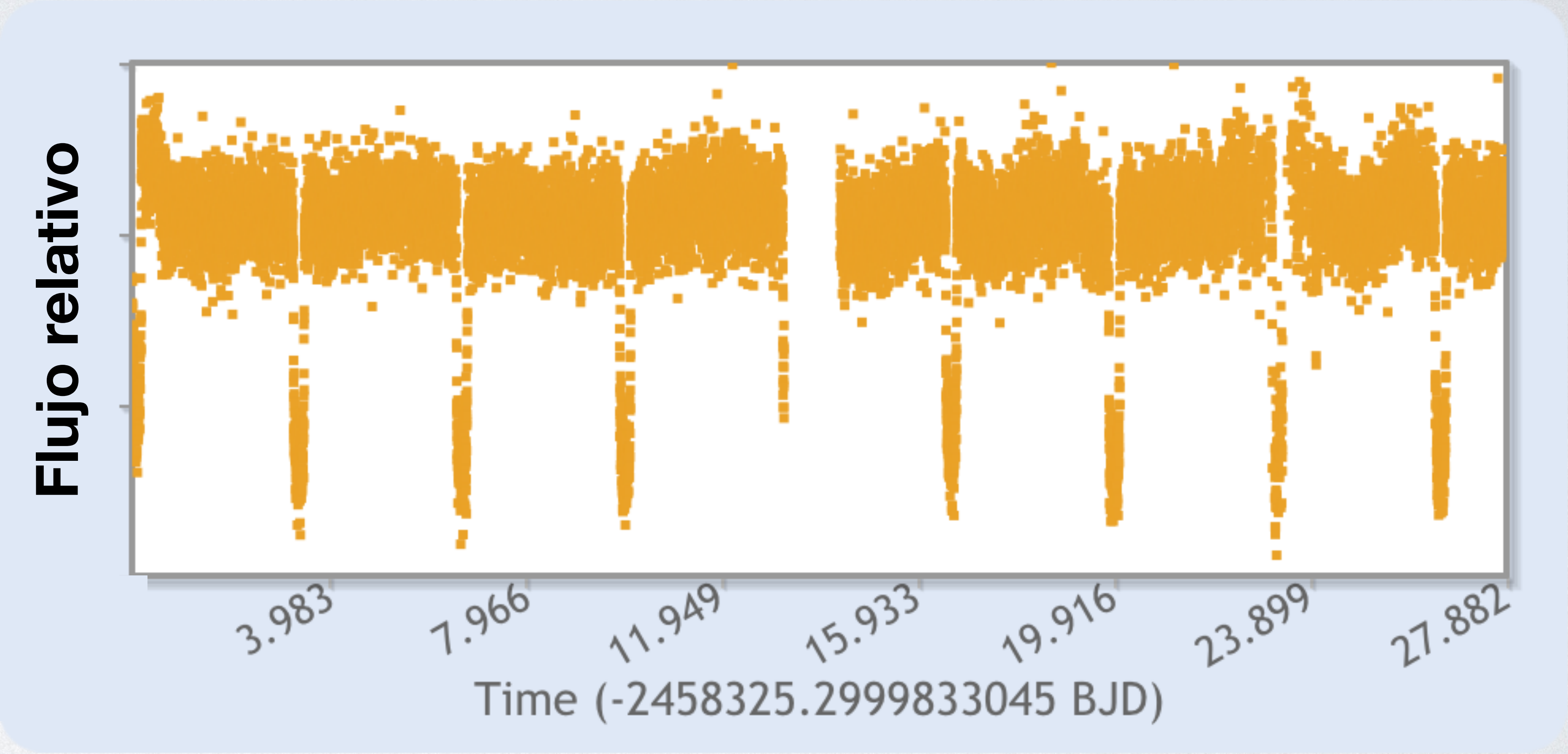
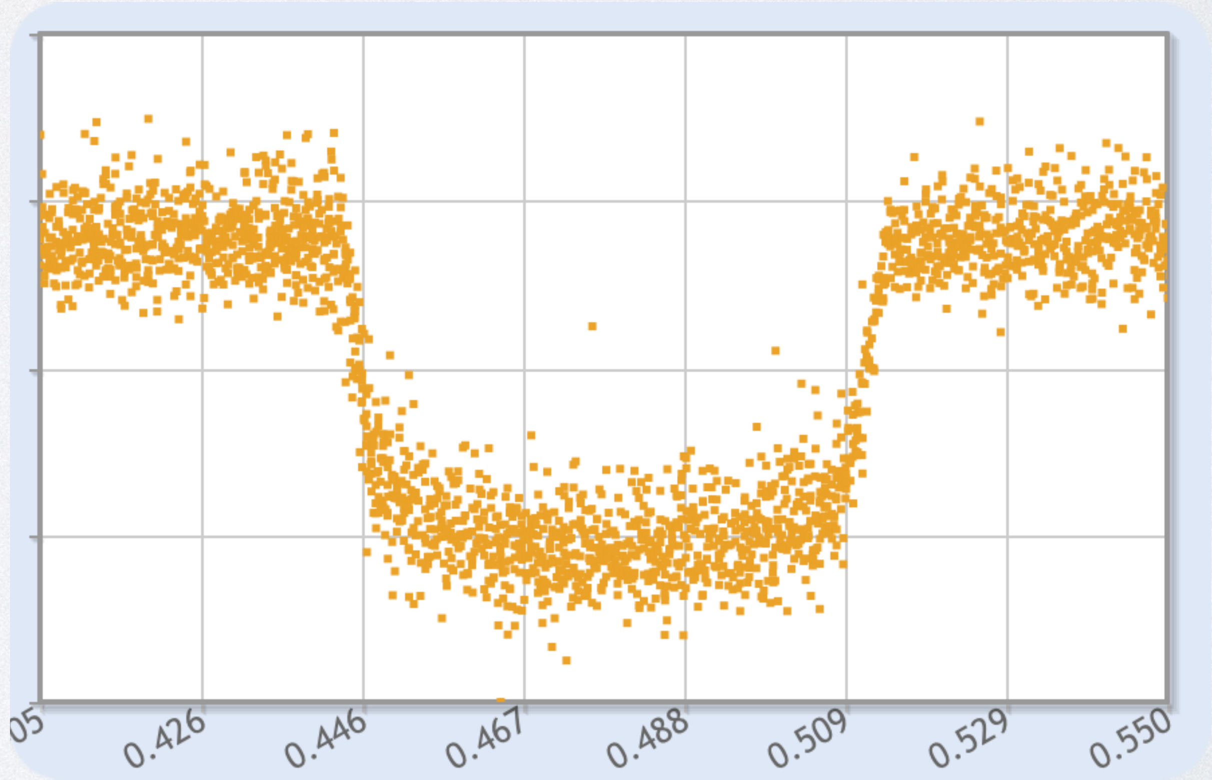
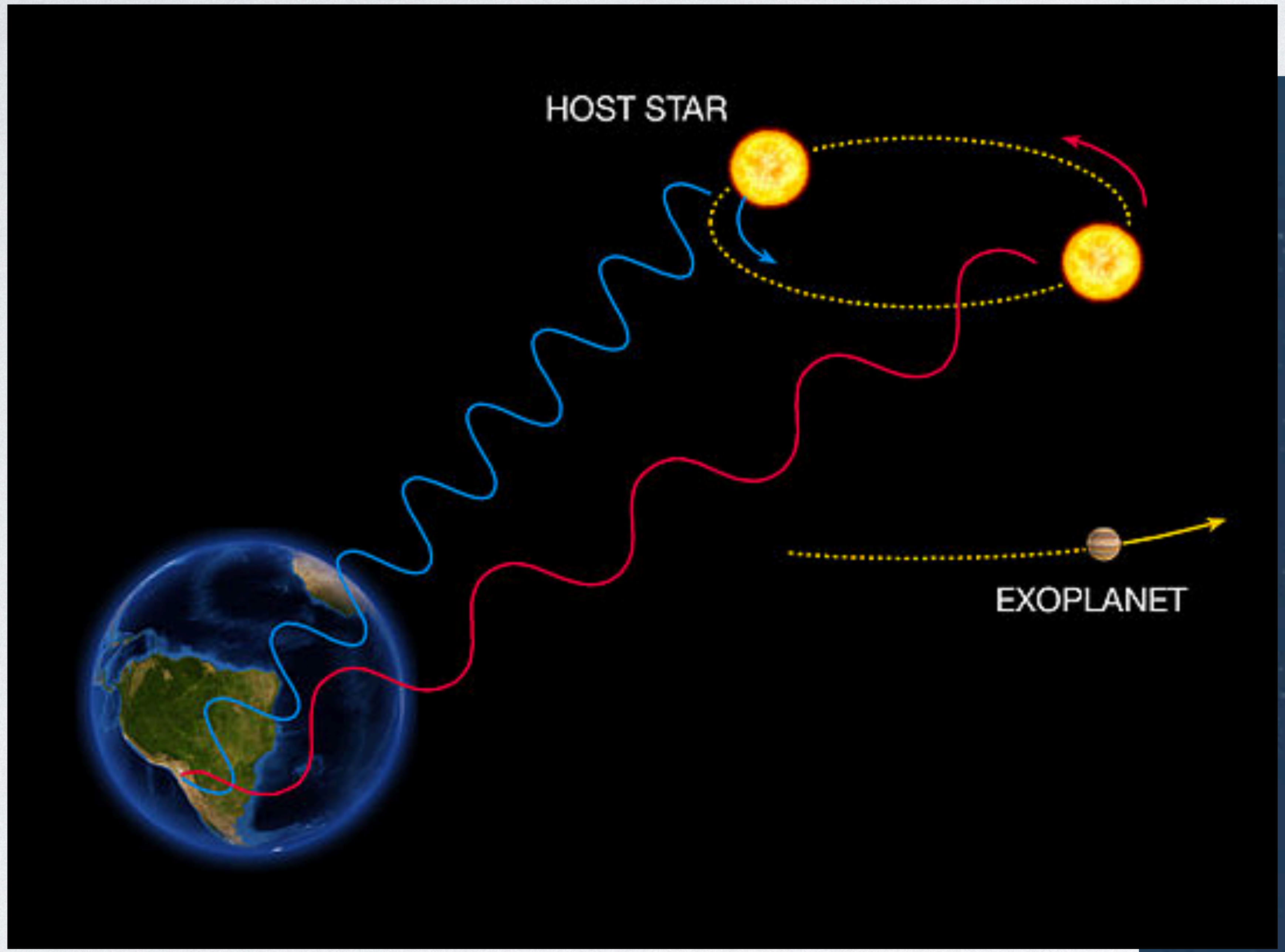


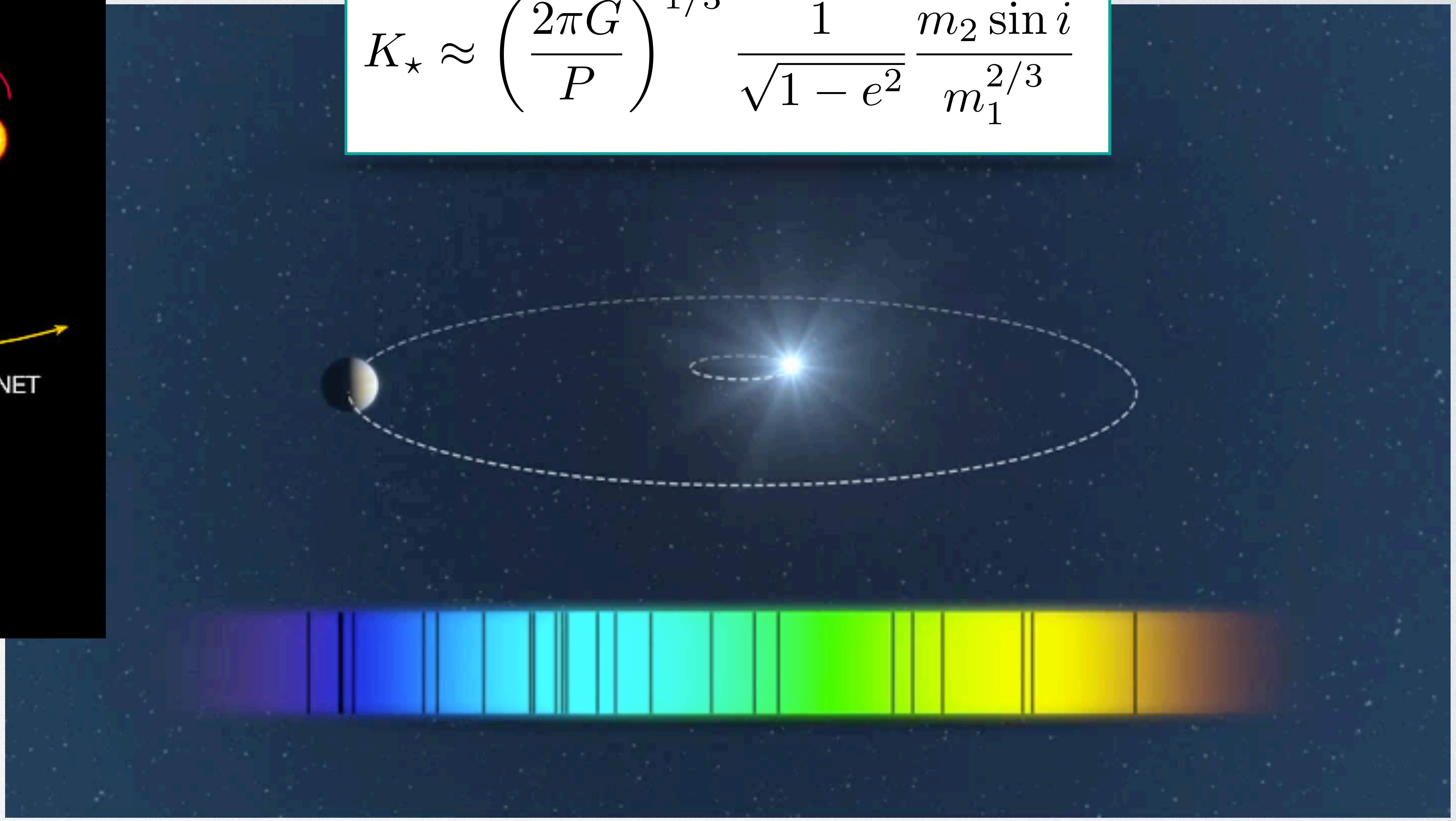


RADIAL VELOCITY METHOD



Credit: ESO

$$K_\star \approx \left(\frac{2\pi G}{P}\right)^{1/3} \frac{1}{\sqrt{1-e^2}} \frac{m_2 \sin i}{m_1^{2/3}}$$



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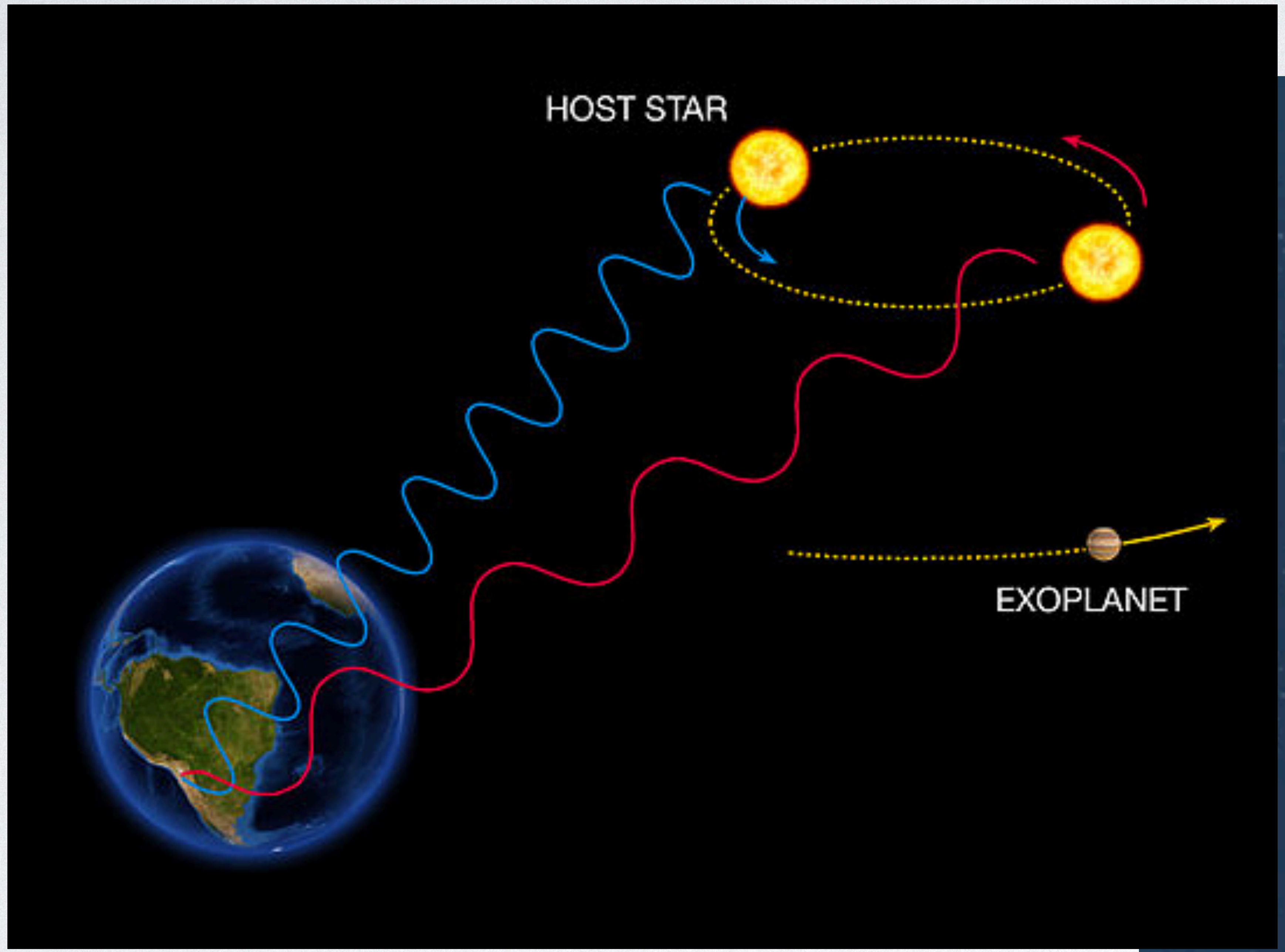

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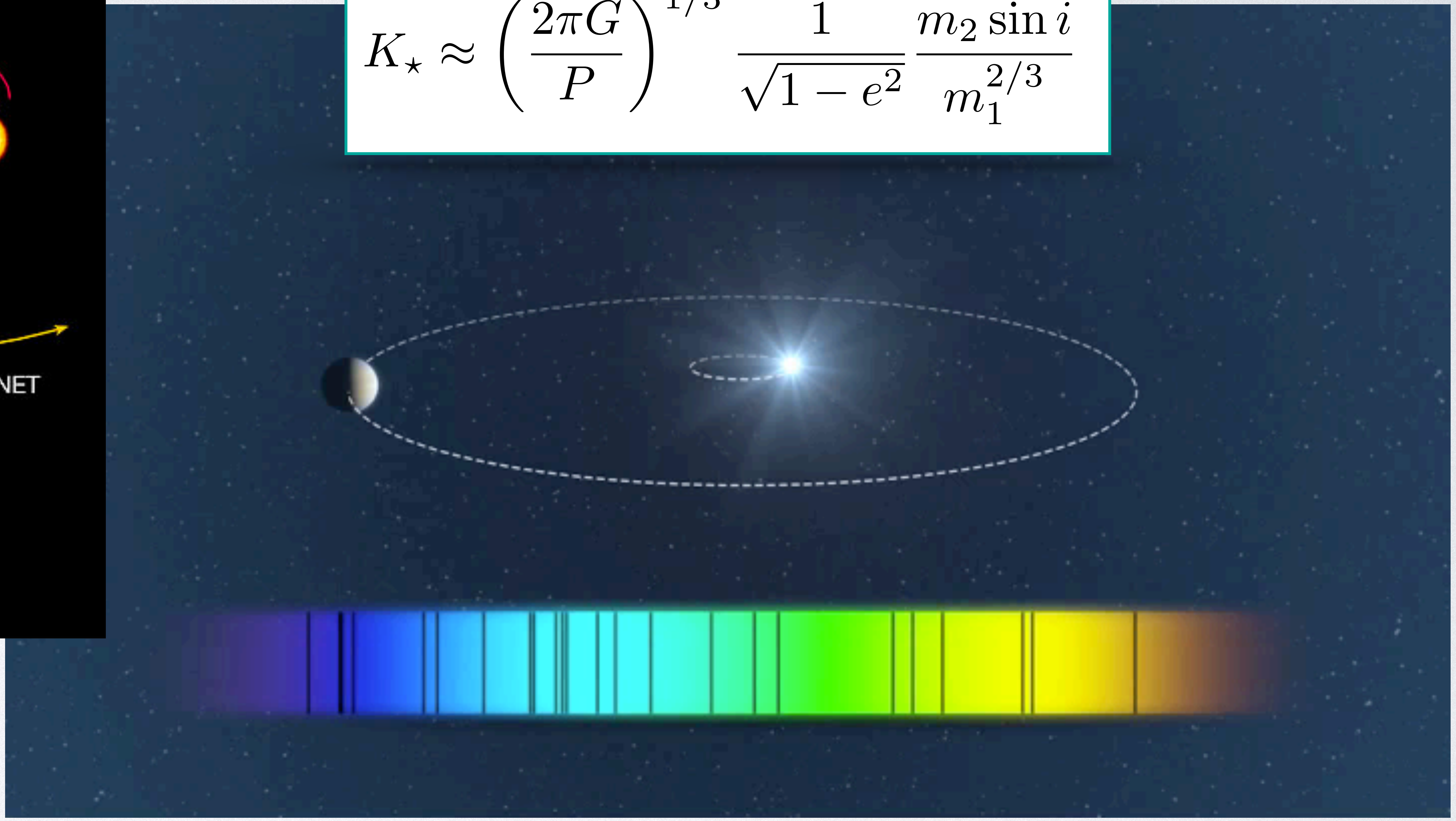

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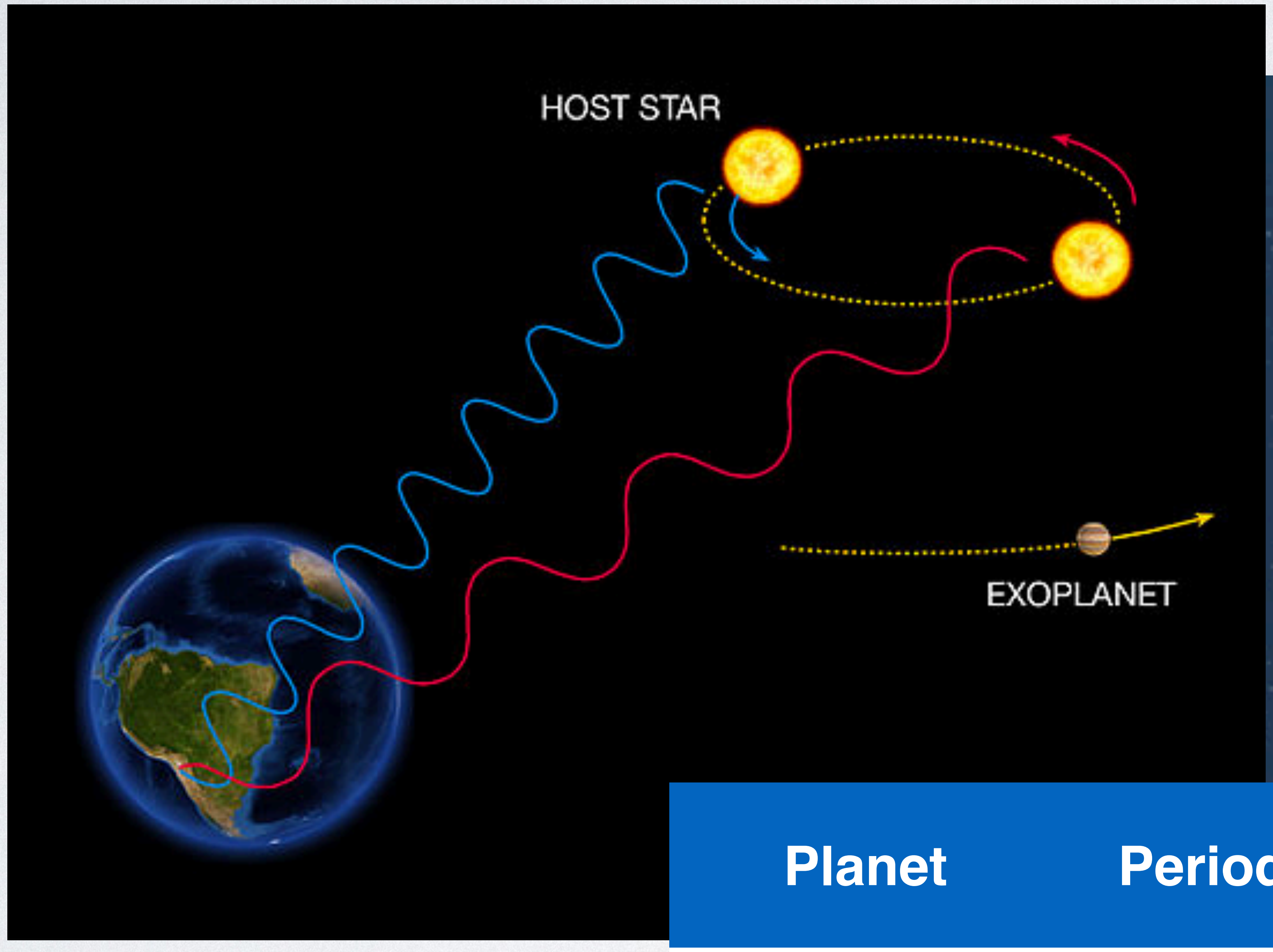
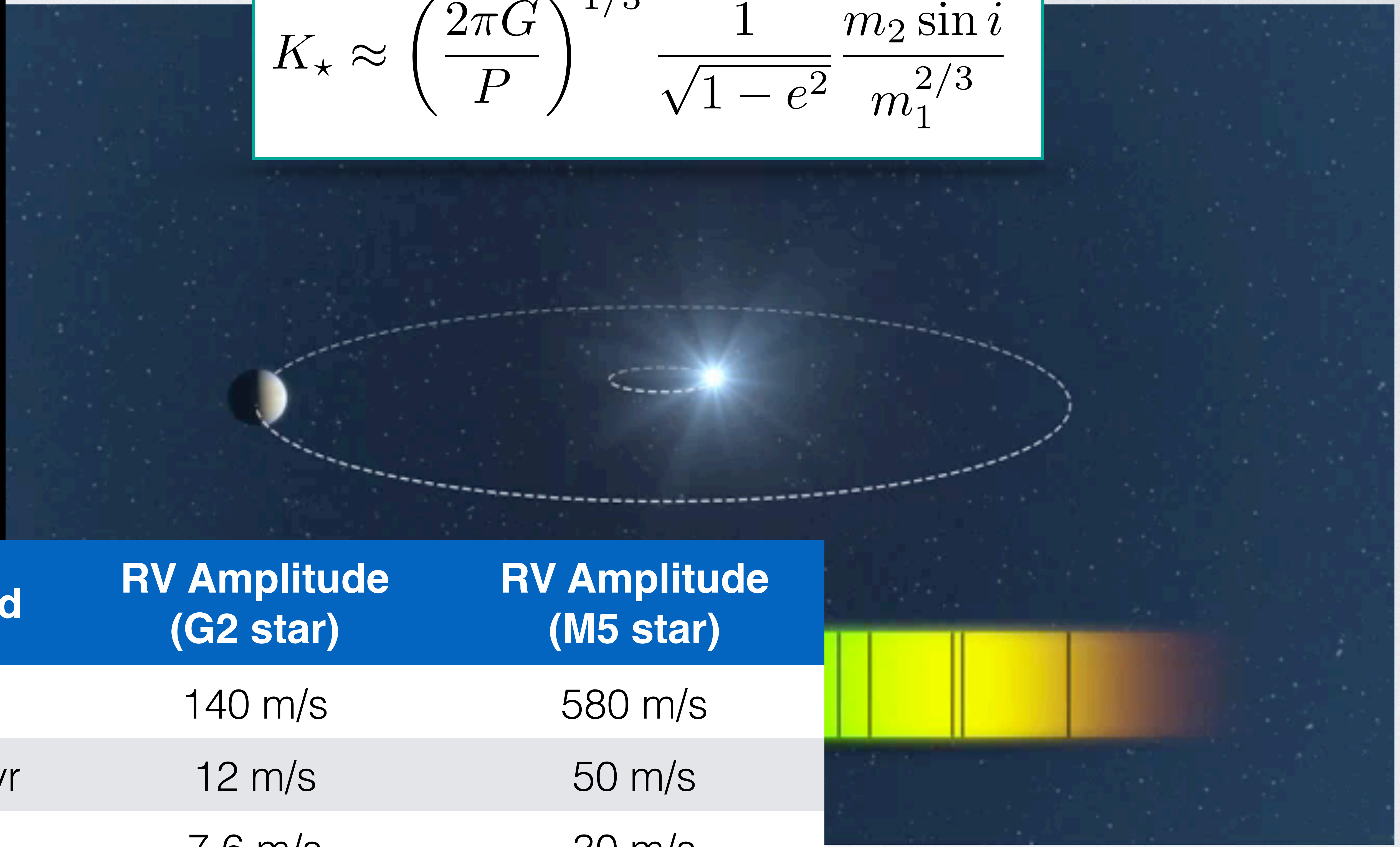
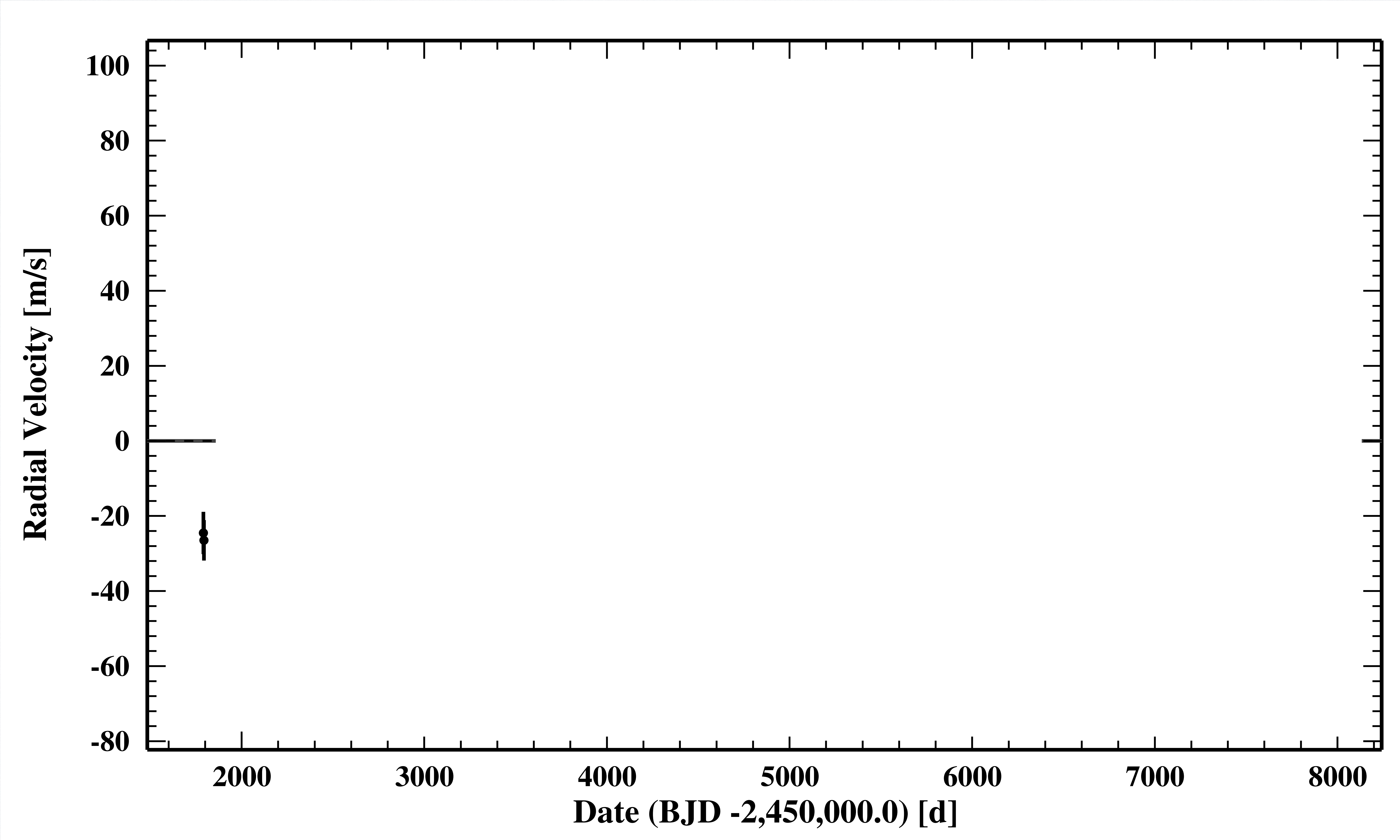




$$K_\star \approx \left(\frac{2\pi G}{P}\right)^{1/3} \frac{1}{\sqrt{1-e^2}} \frac{m_2 \sin i}{m_1^{2/3}}$$

Planet	Period	RV Amplitude (G2 star)	RV Amplitude (M5 star)
Jupiter	3 d	140 m/s	580 m/s
Jupiter	11.9 yr	12 m/s	50 m/s
Neptune	3 d	7.6 m/s	30 m/s
Earth	3 d	44 cm/s	1.8 m/s
Earth	1 yr	9 cm/s	40 cm/s

RADIAL VELOCITY TIME SERIES



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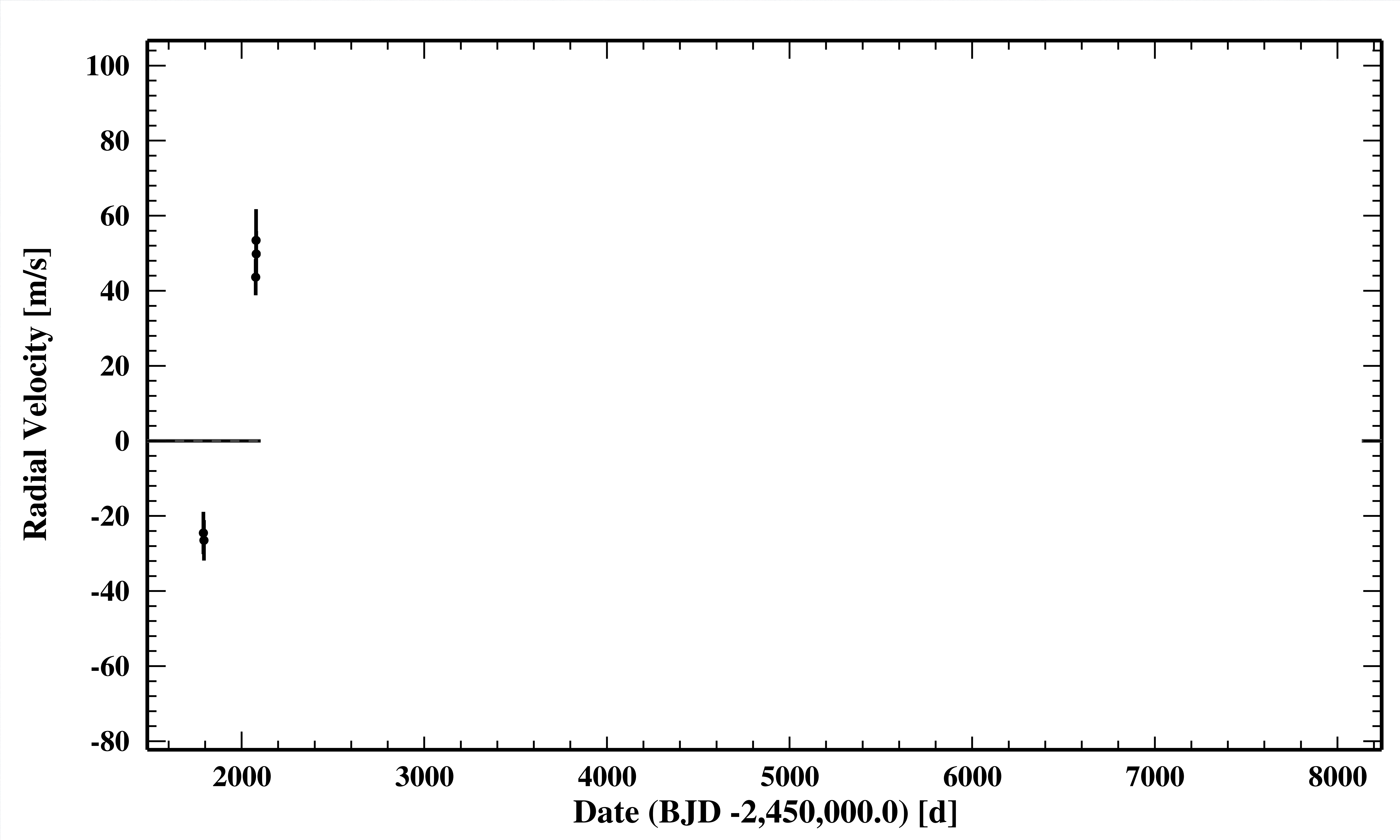

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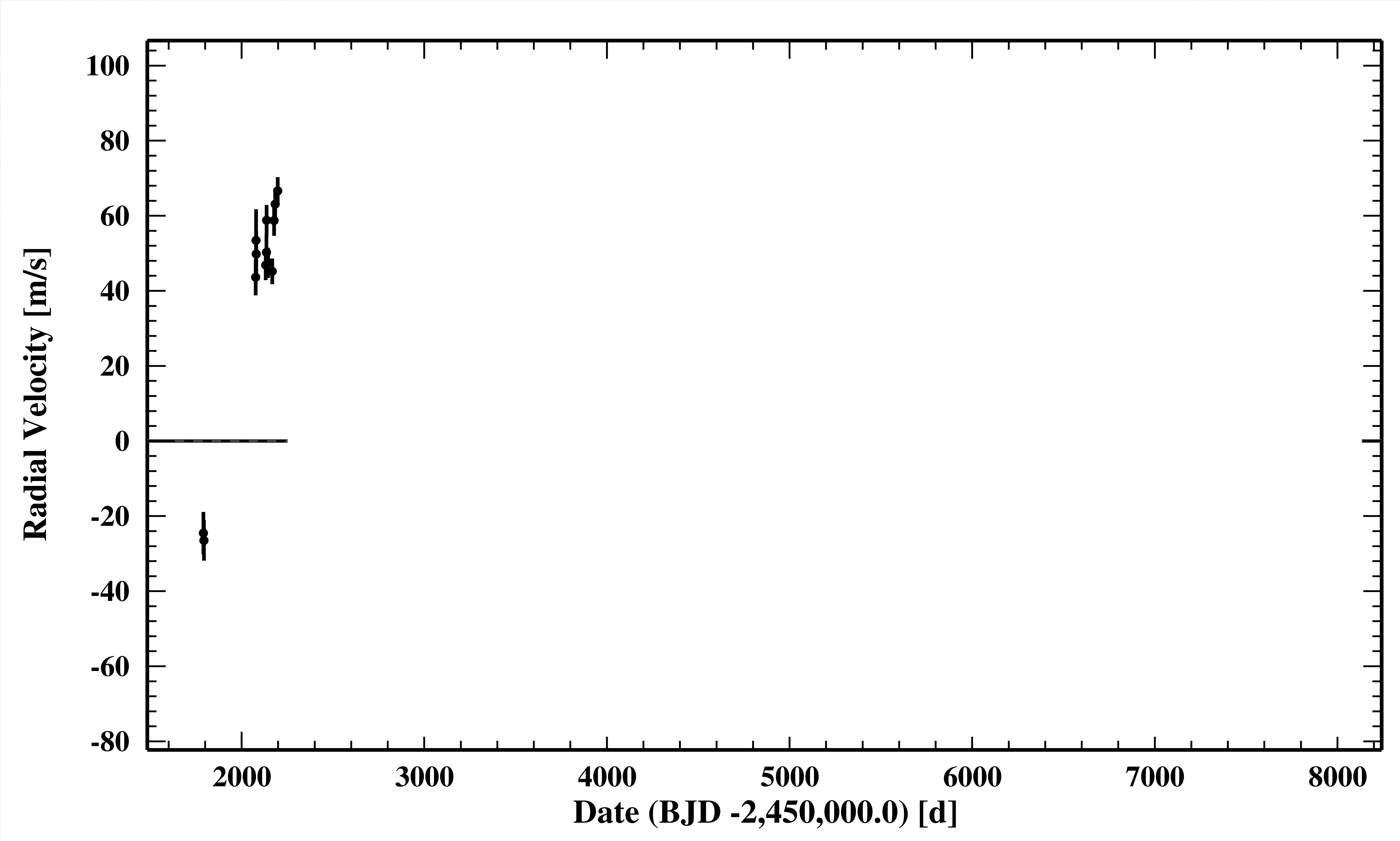

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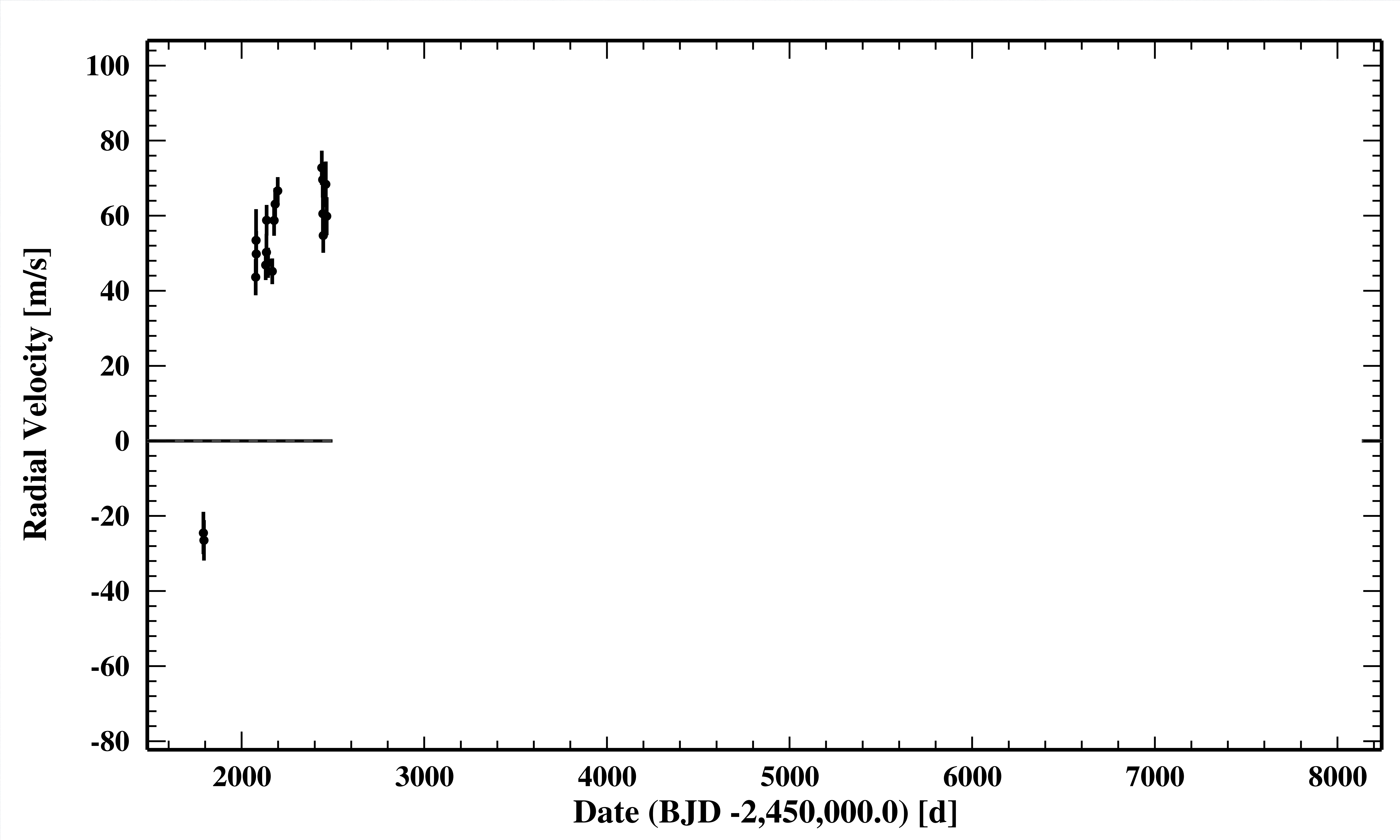

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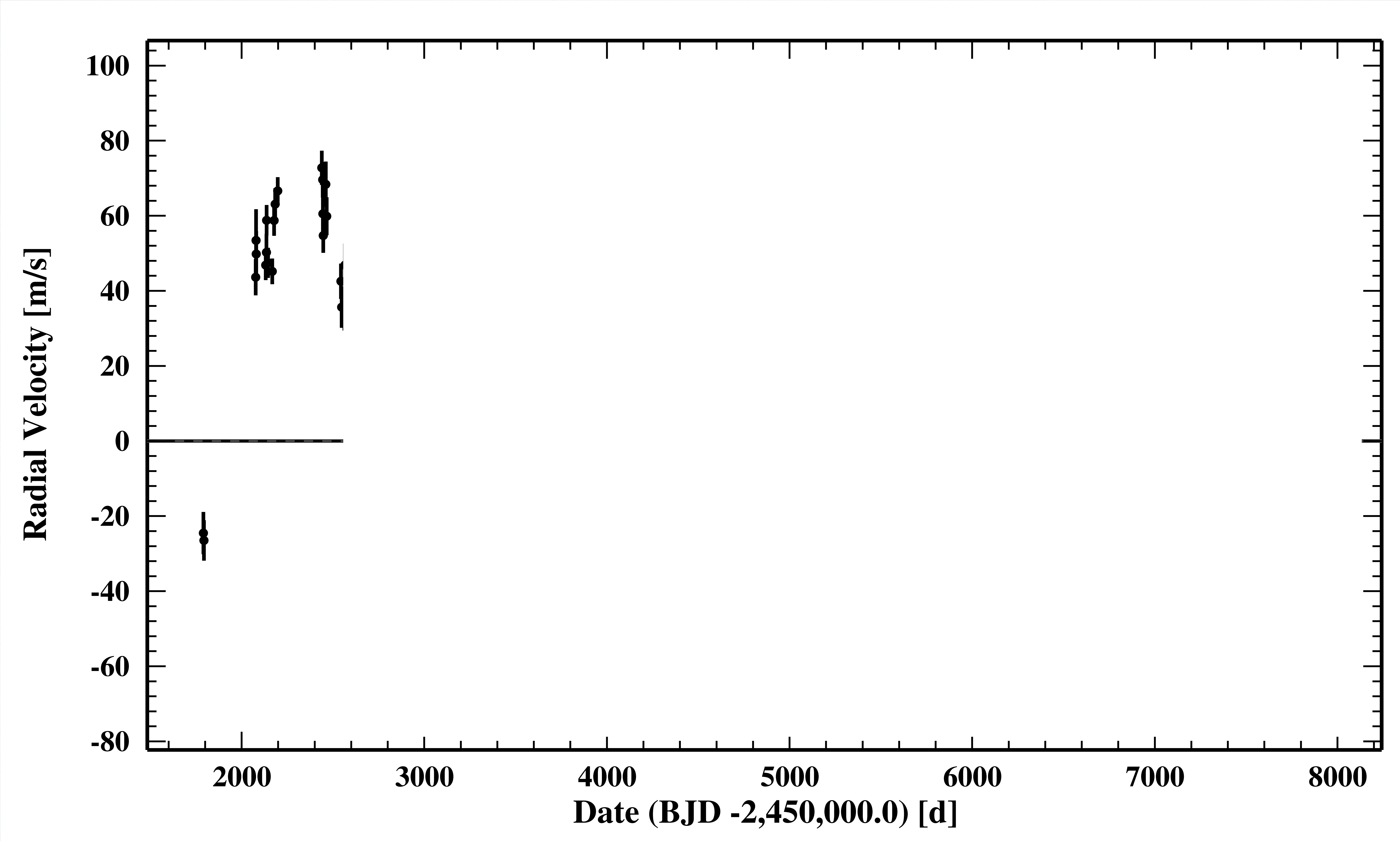

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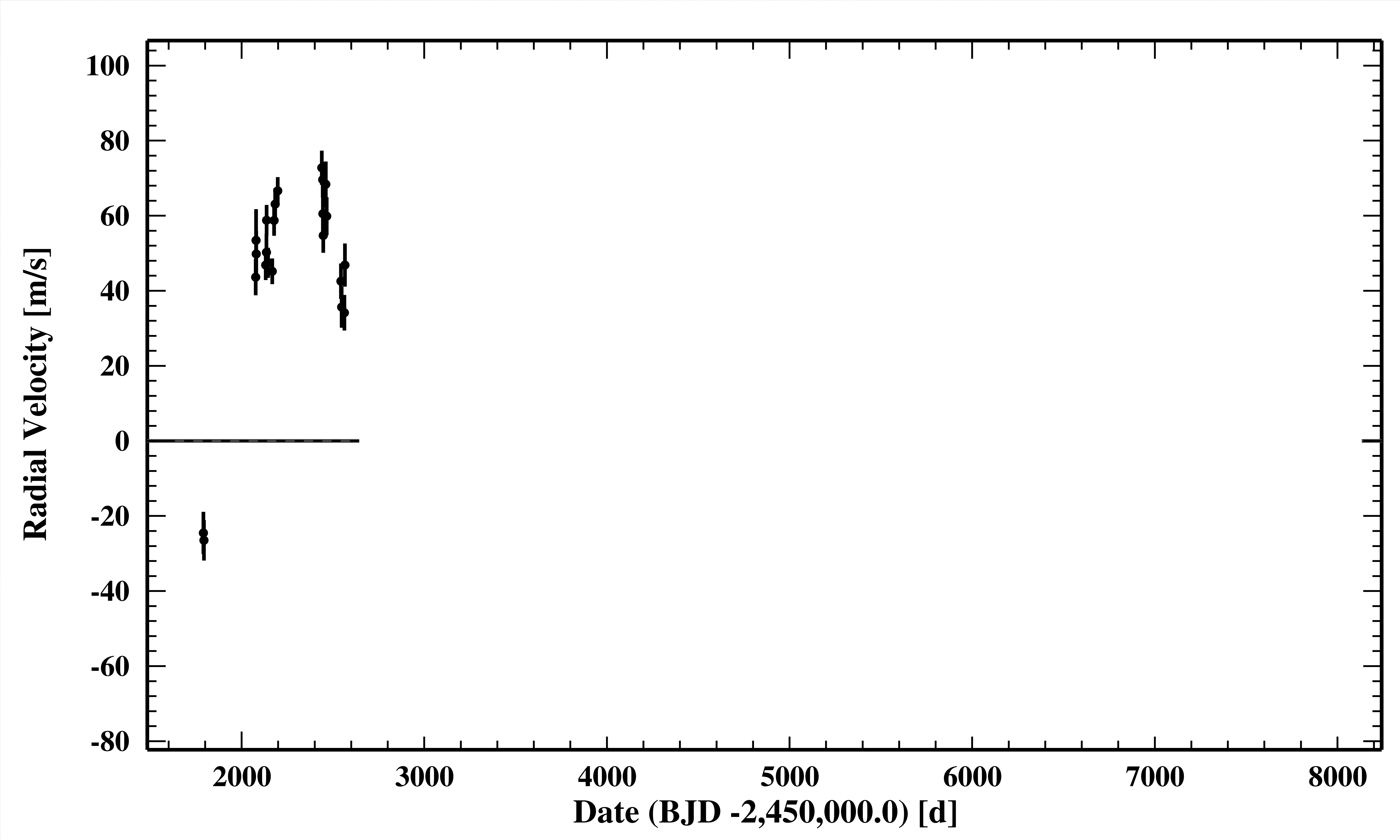

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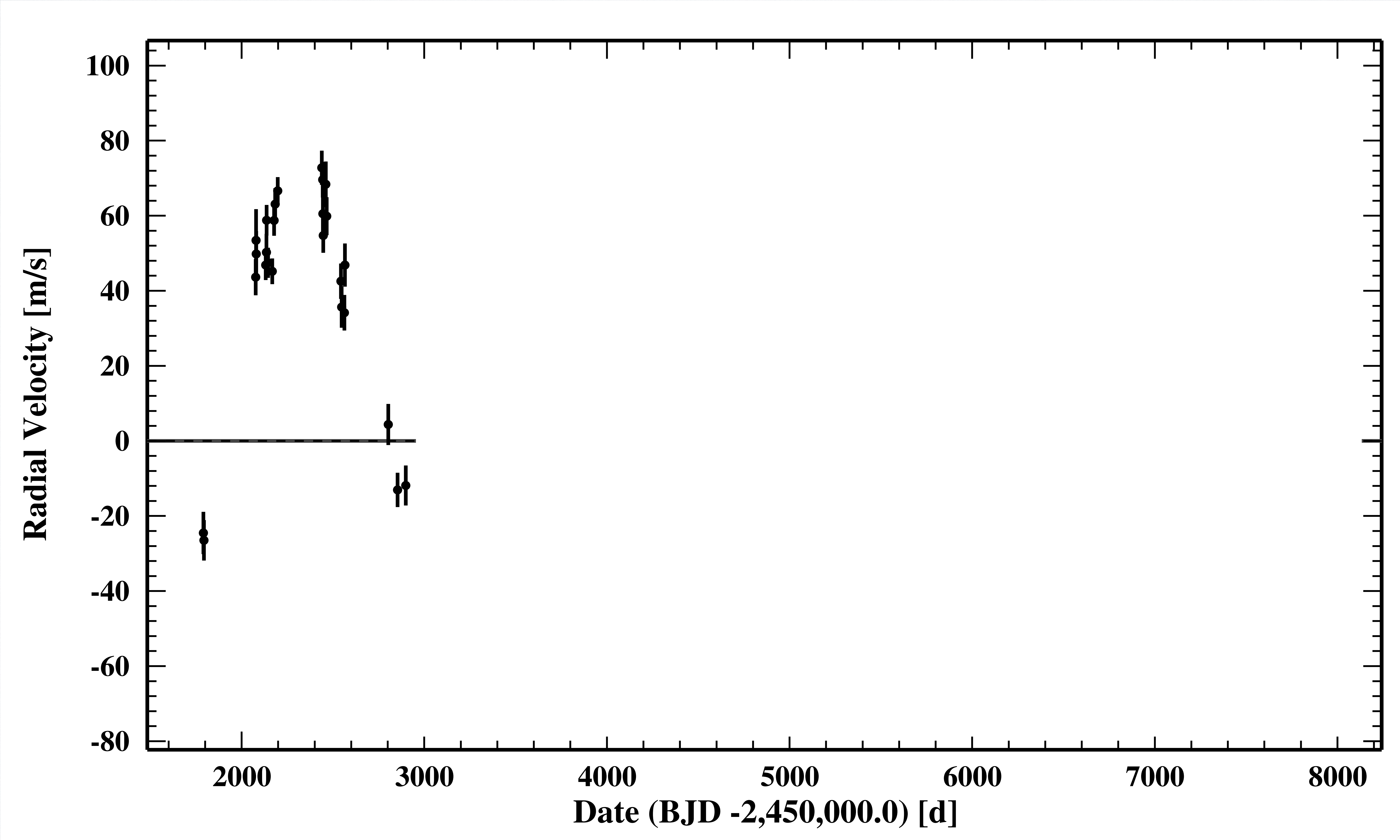

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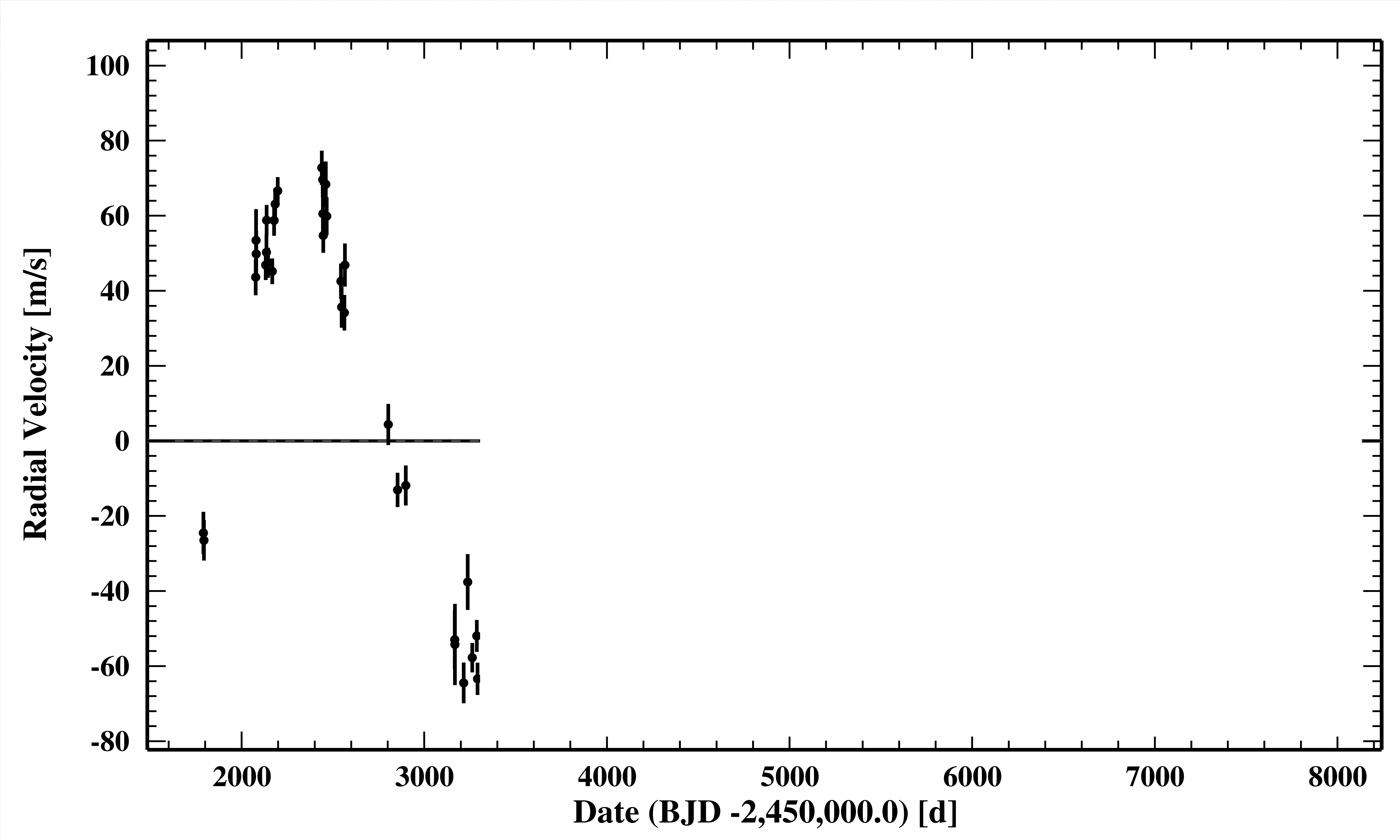

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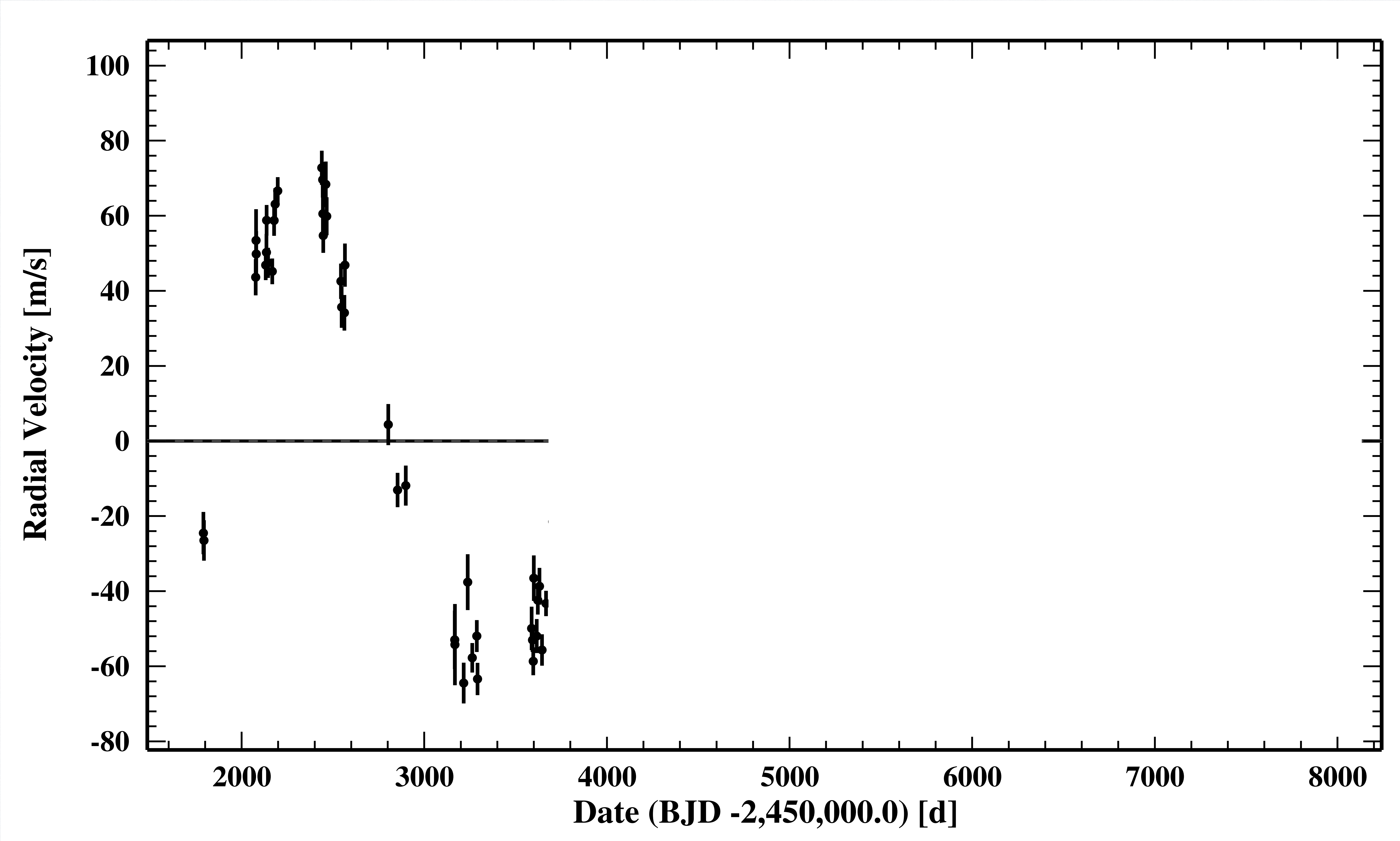

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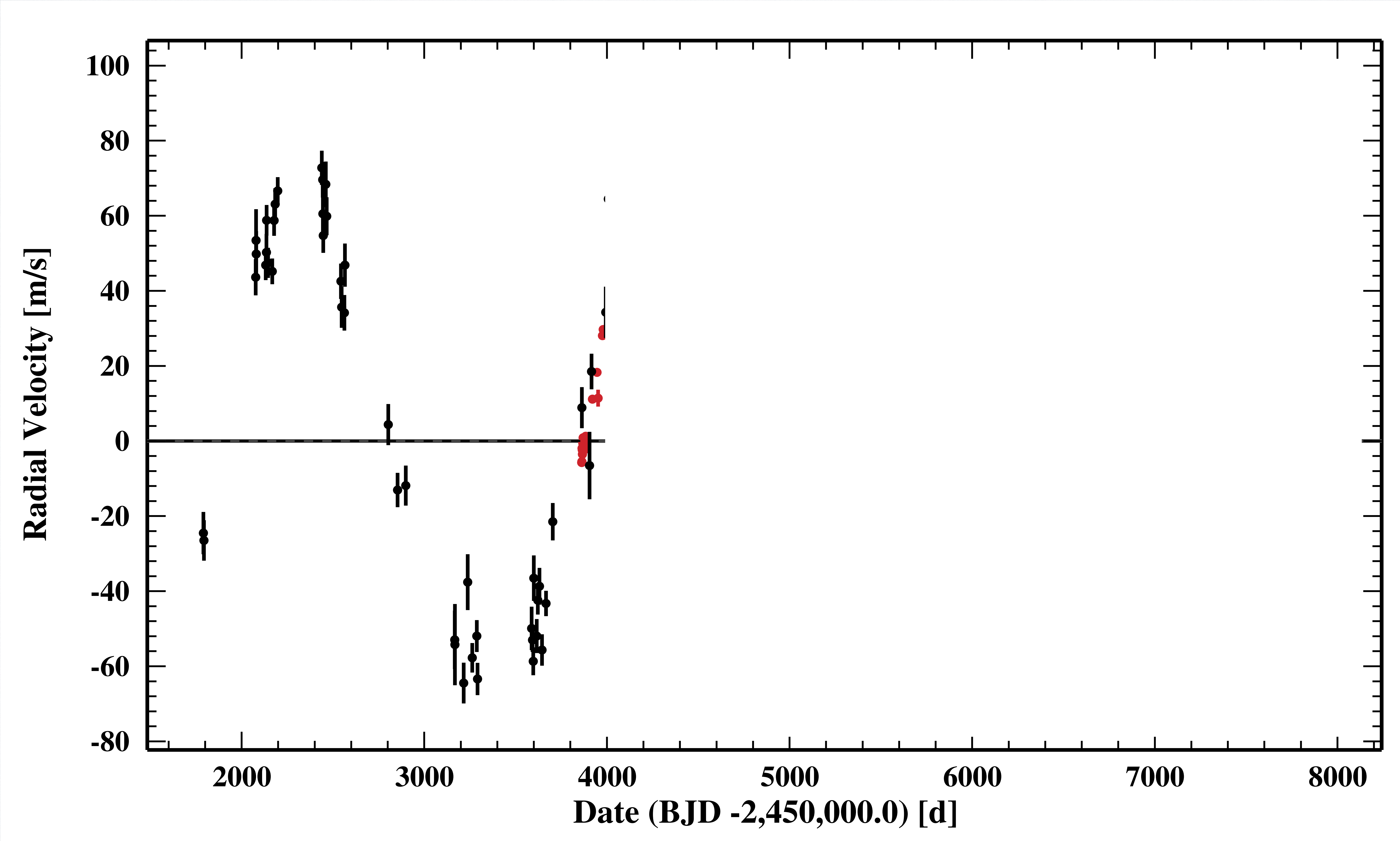

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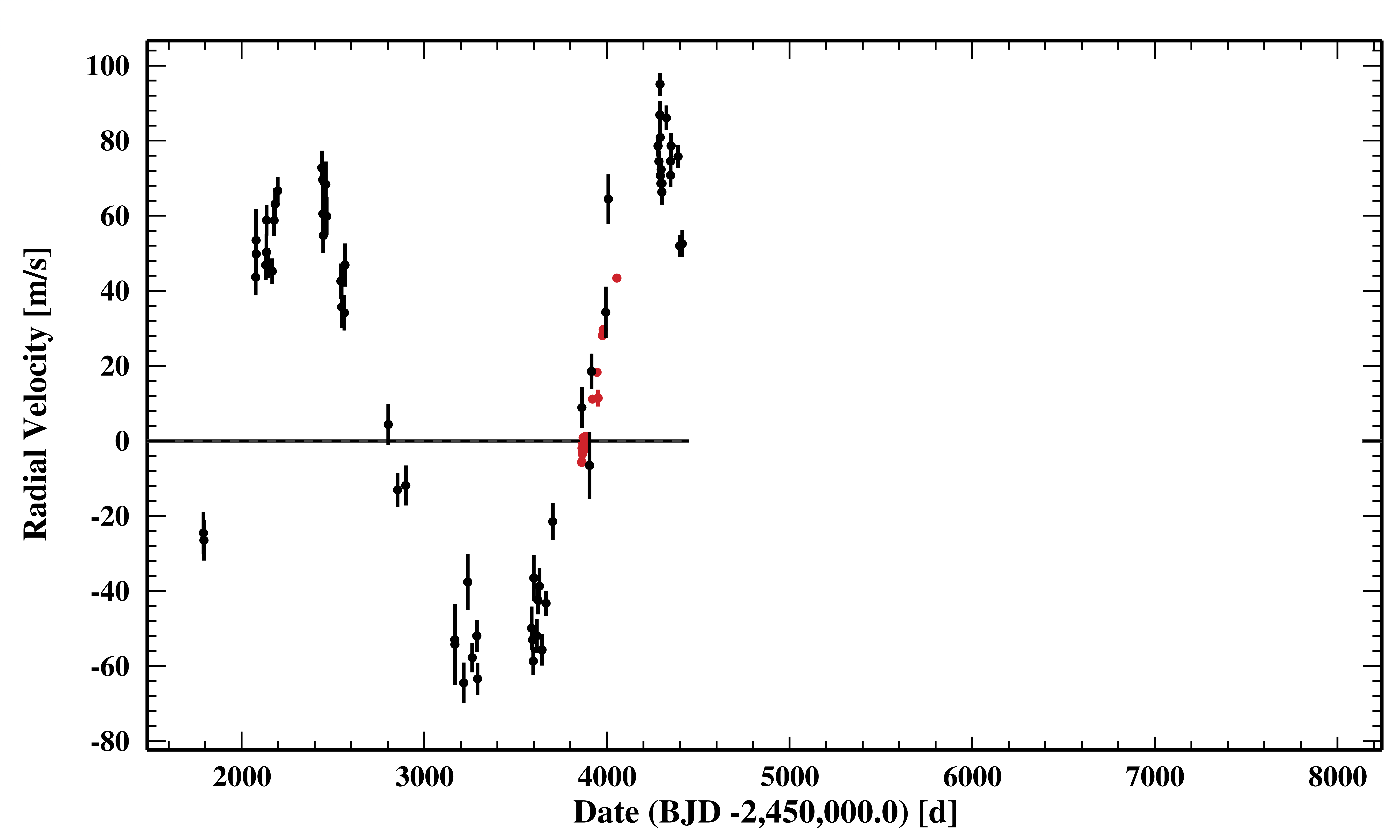

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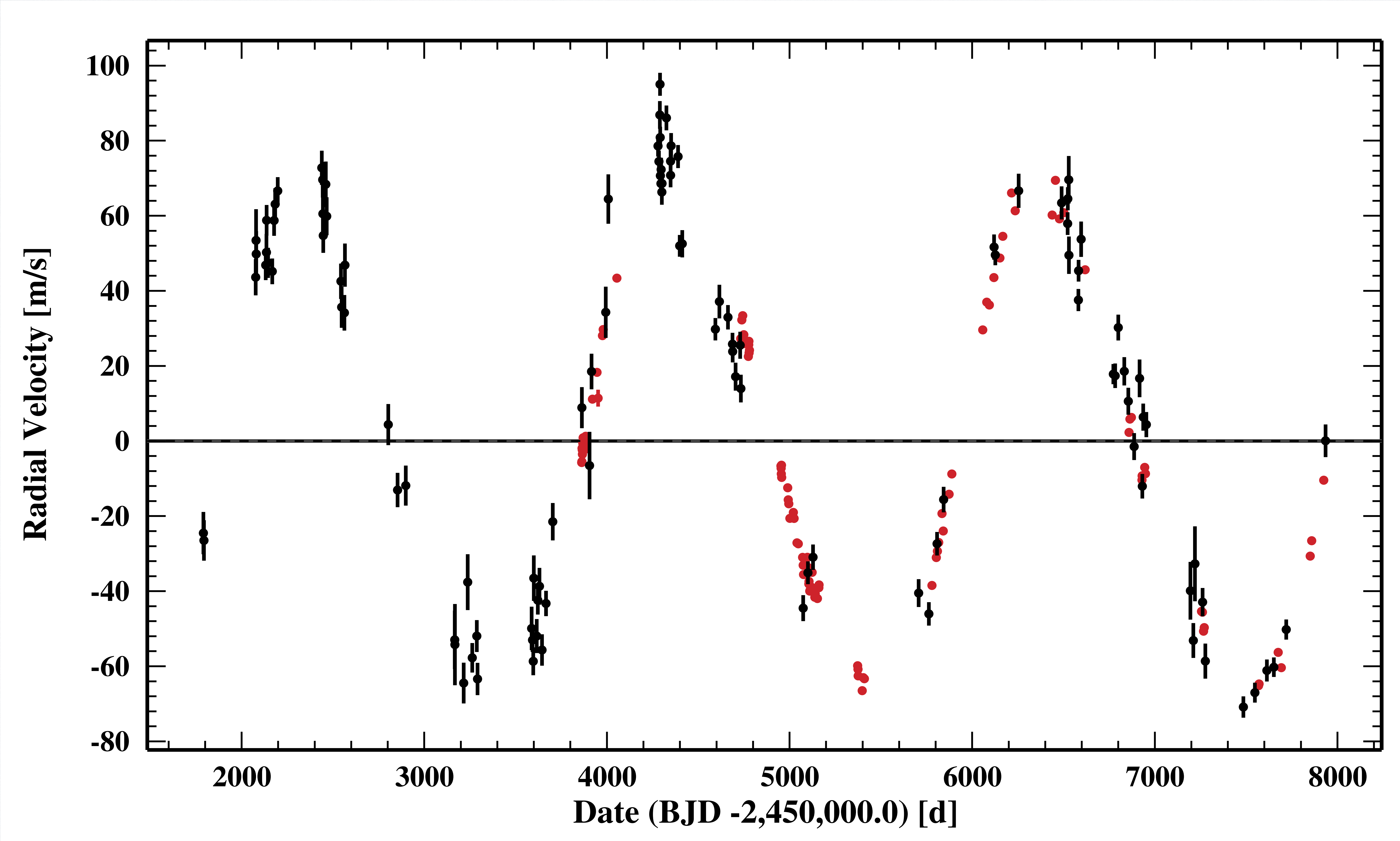

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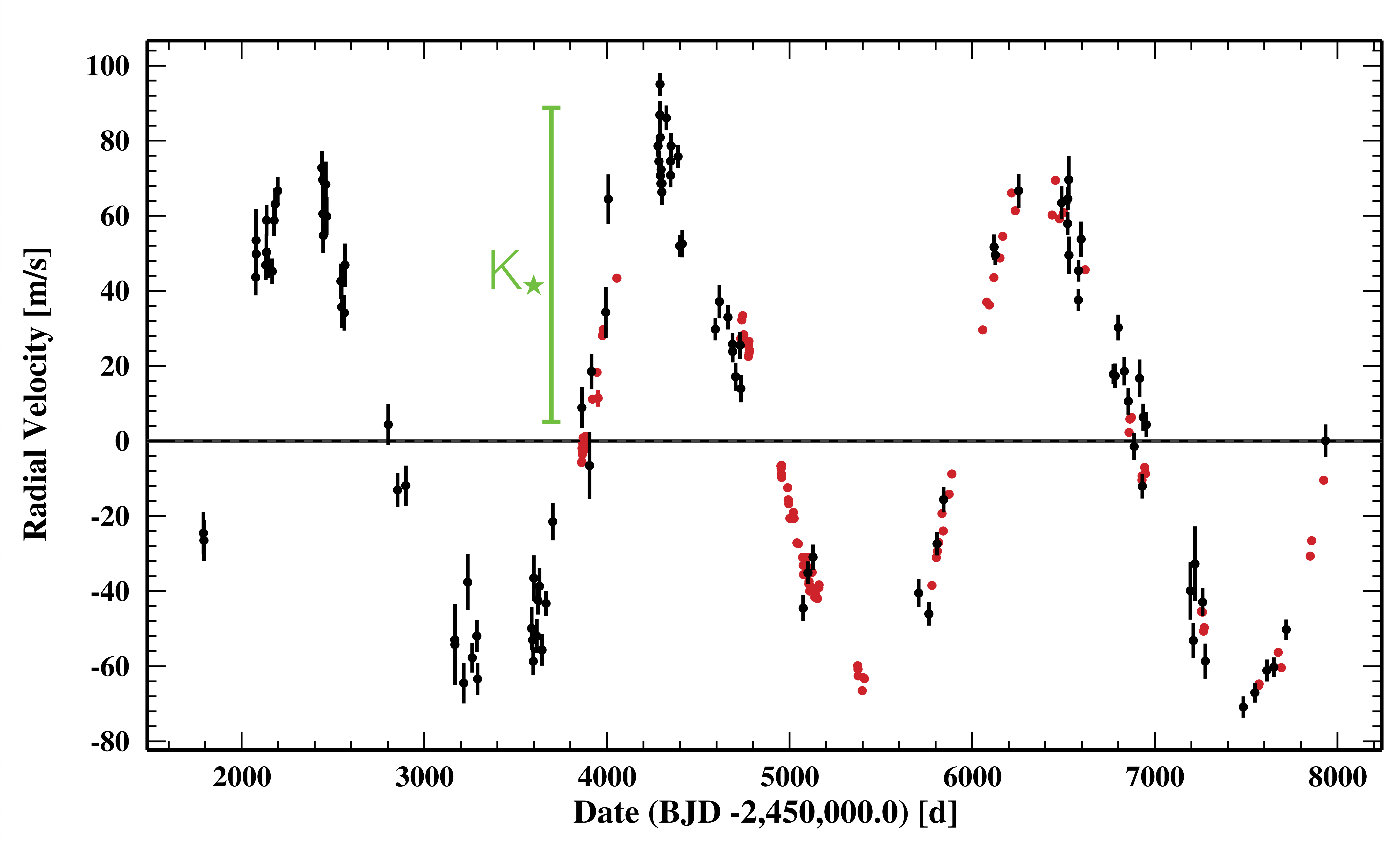

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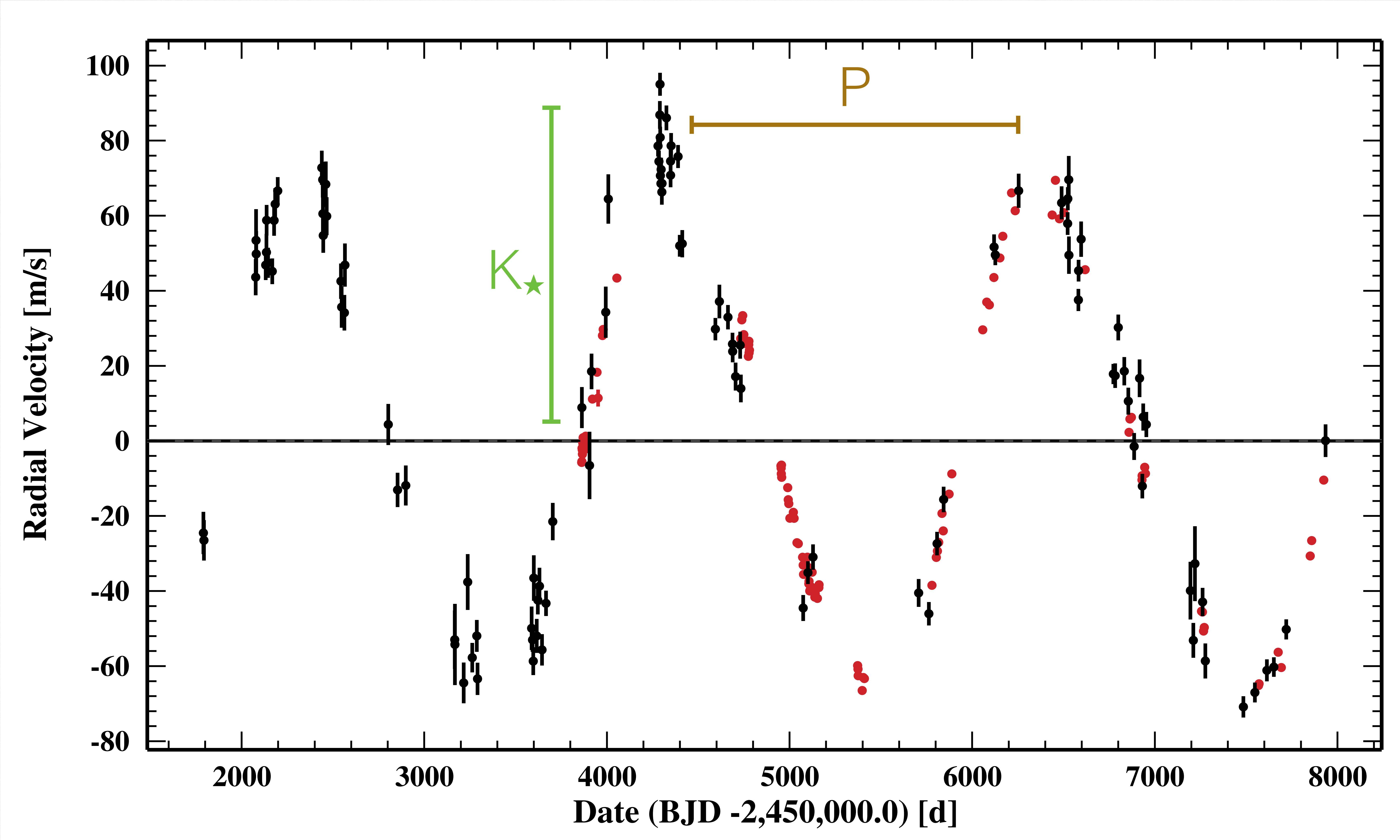
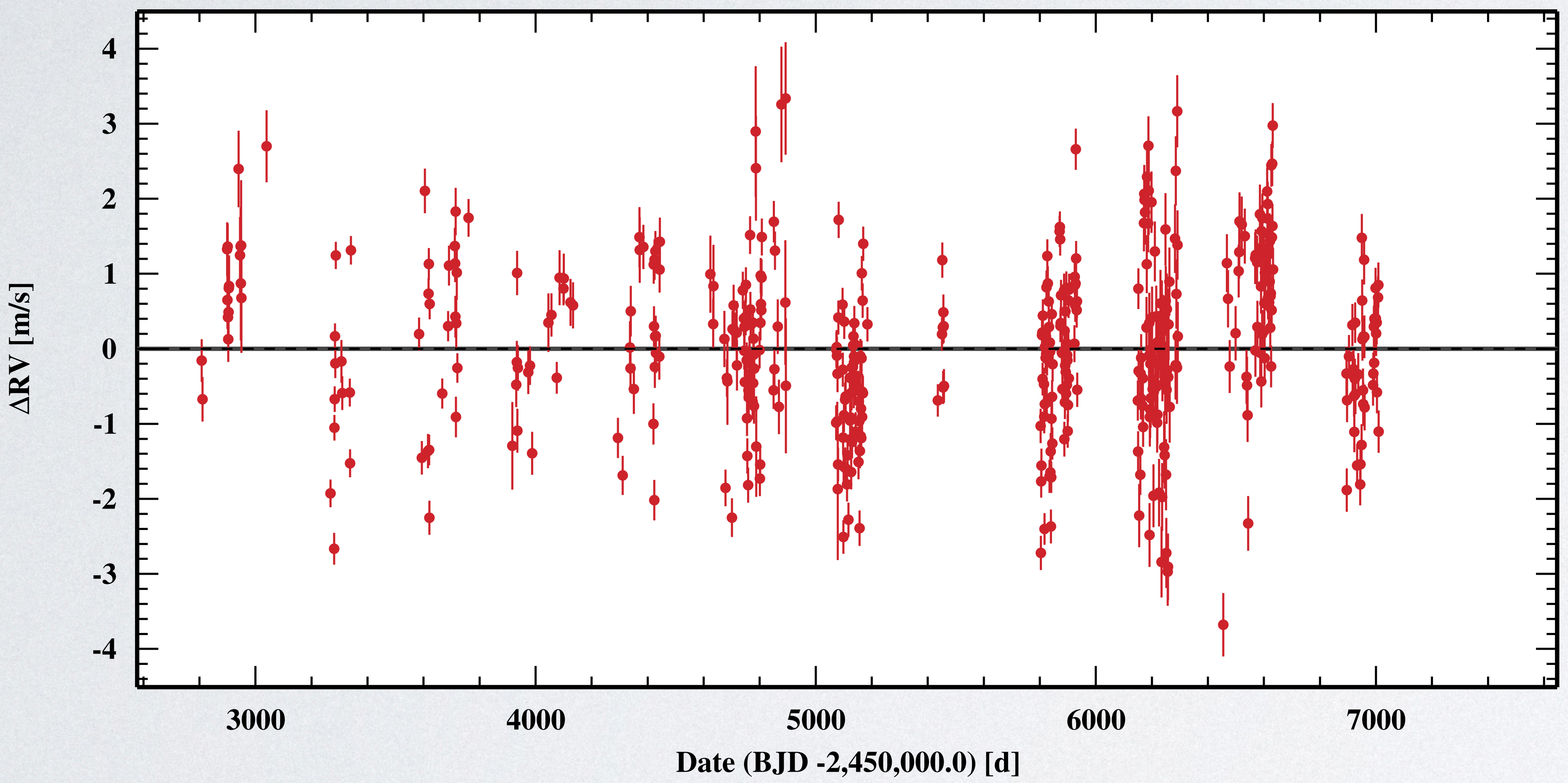


THE GLS PERIODOGRAM

The classical approach to detecting signals in RV time series

Generalised Lomb Scargle (GLS): Sort of Fourier Transform for unevenly sampled data.

$$p(\omega) = \frac{\chi_0^2 - \chi_\omega^2}{\chi_0^2}$$



Lomb (1976)
Scargle (1982)
Baluev (2008, 2013)
Zehcmeister & Kürster (2009)
Delisle, Ségransan & Hara (2020)

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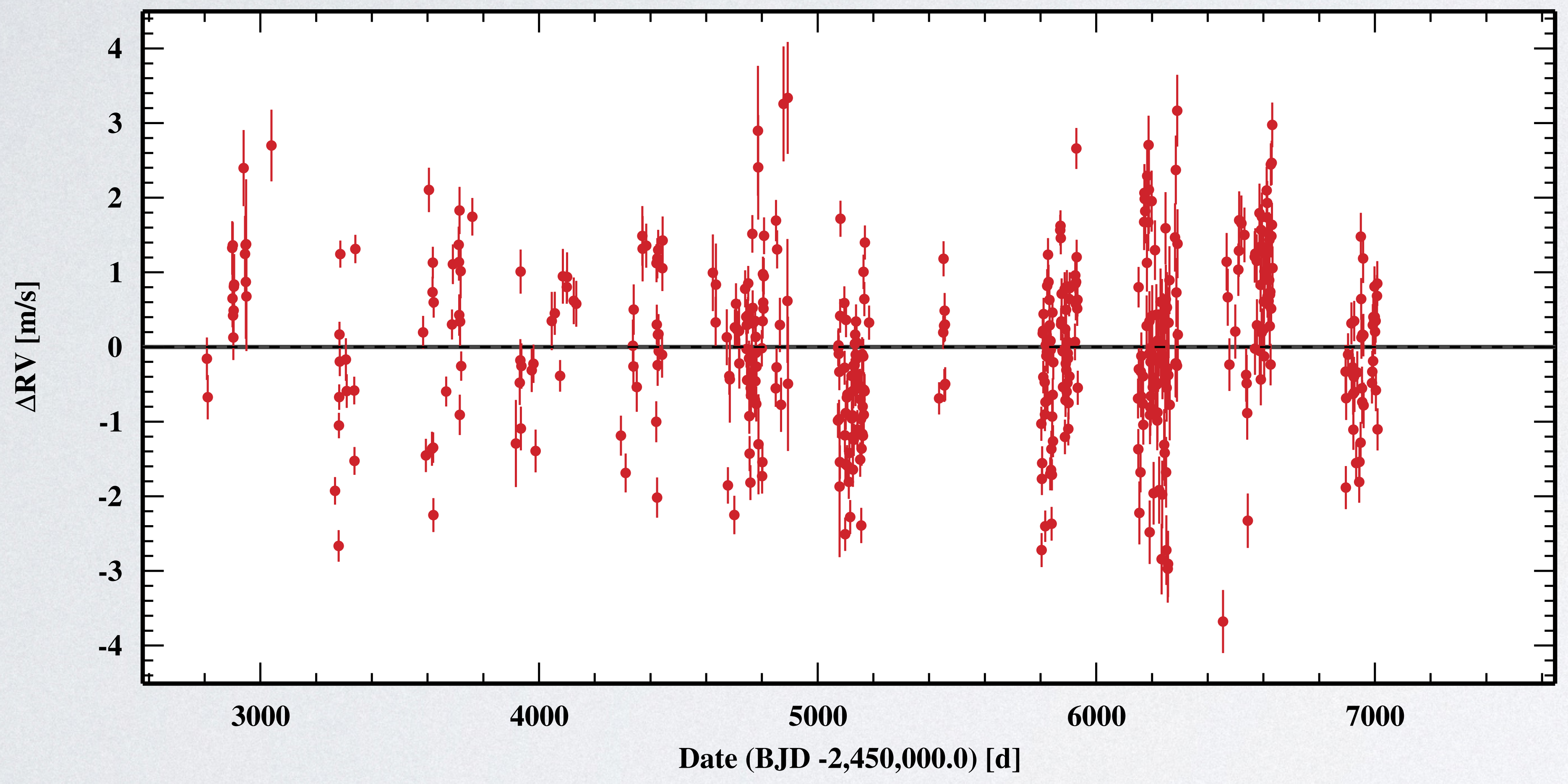

$$p(\omega) = \frac{\chi_0^2 - \chi_\omega^2}{\chi_0^2}$$

χ^2 for a linear sinusoidal model

χ^2 for the weighted mean

$$A\sin(\omega t) + B\cos(\omega t) + C$$

Lomb (1976)
Scargle (1982)
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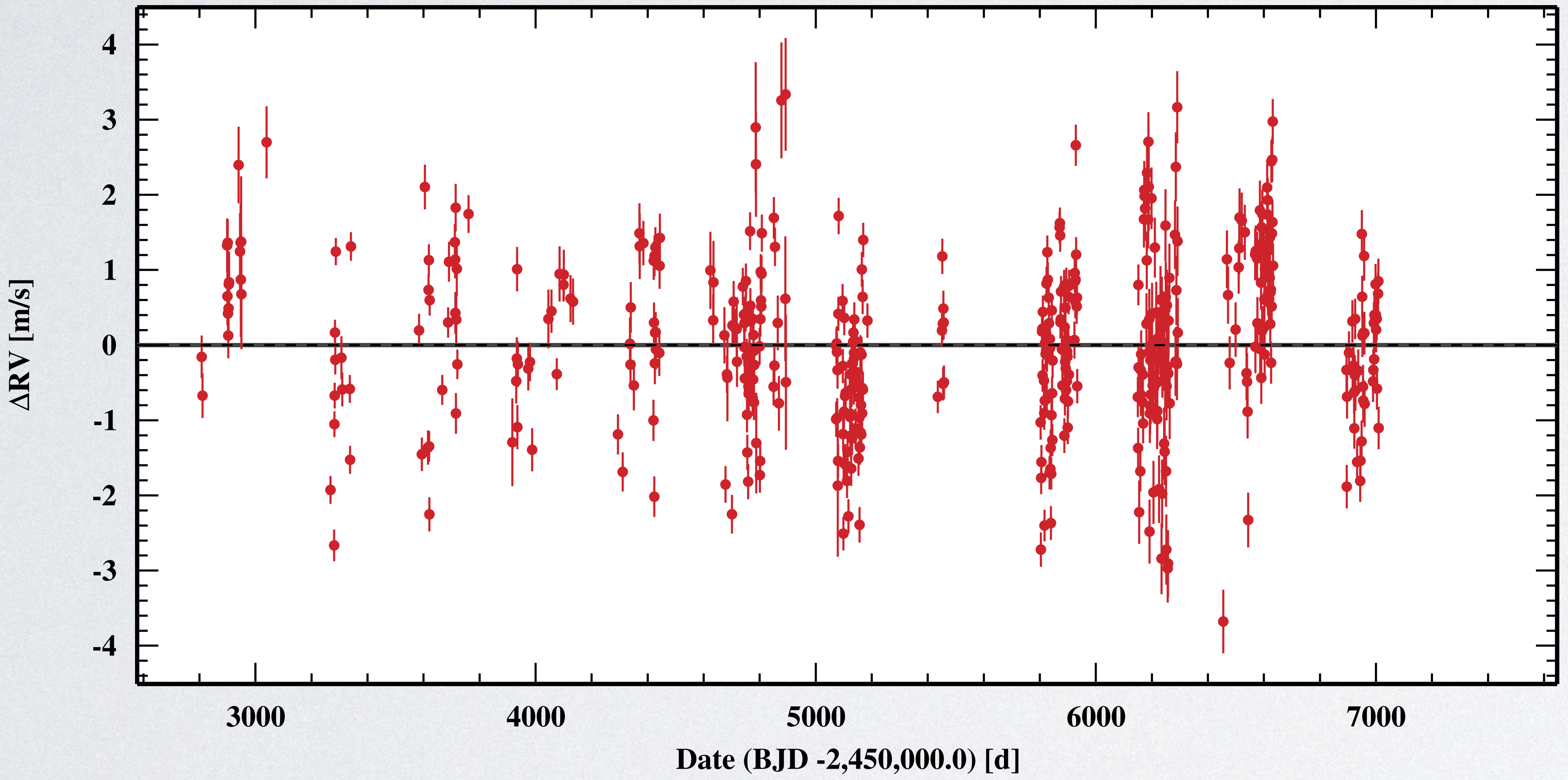

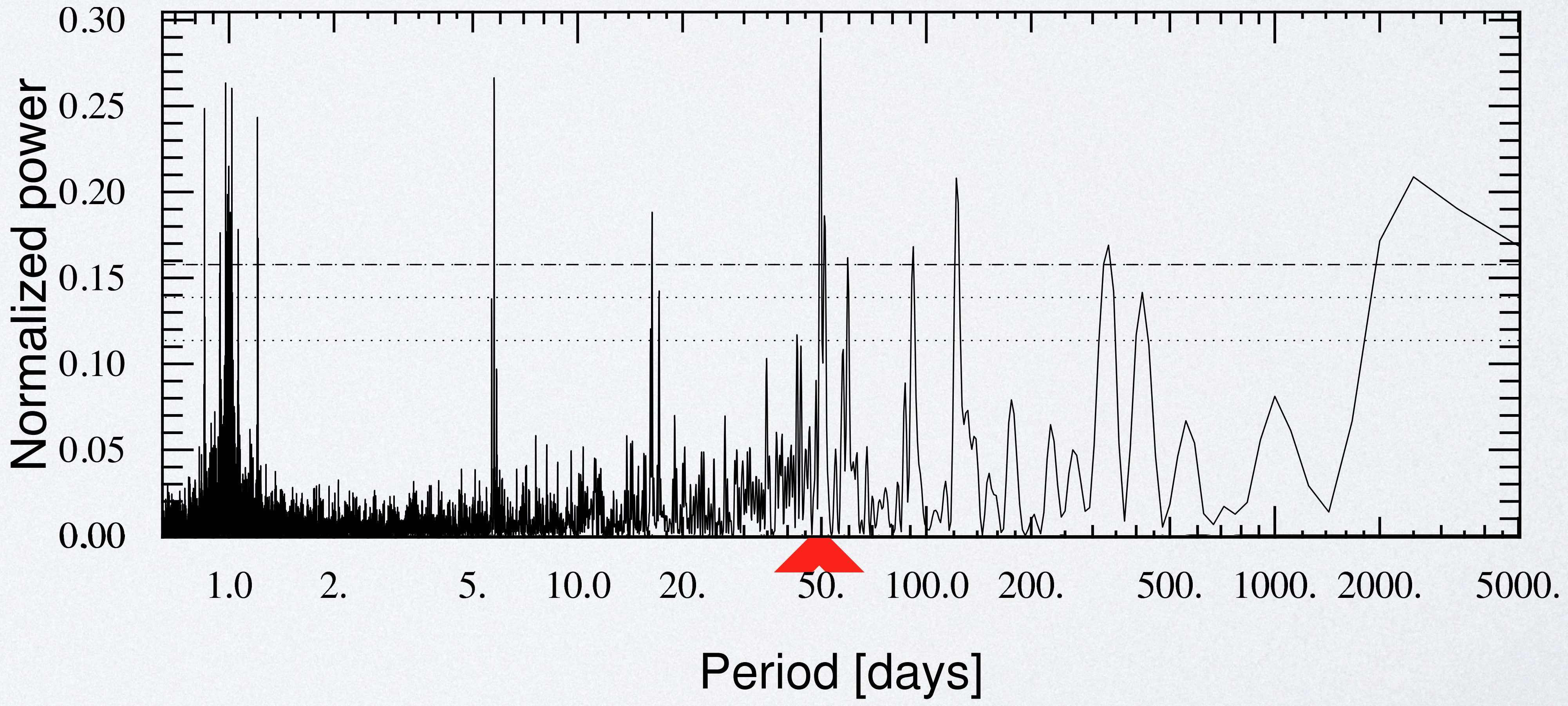

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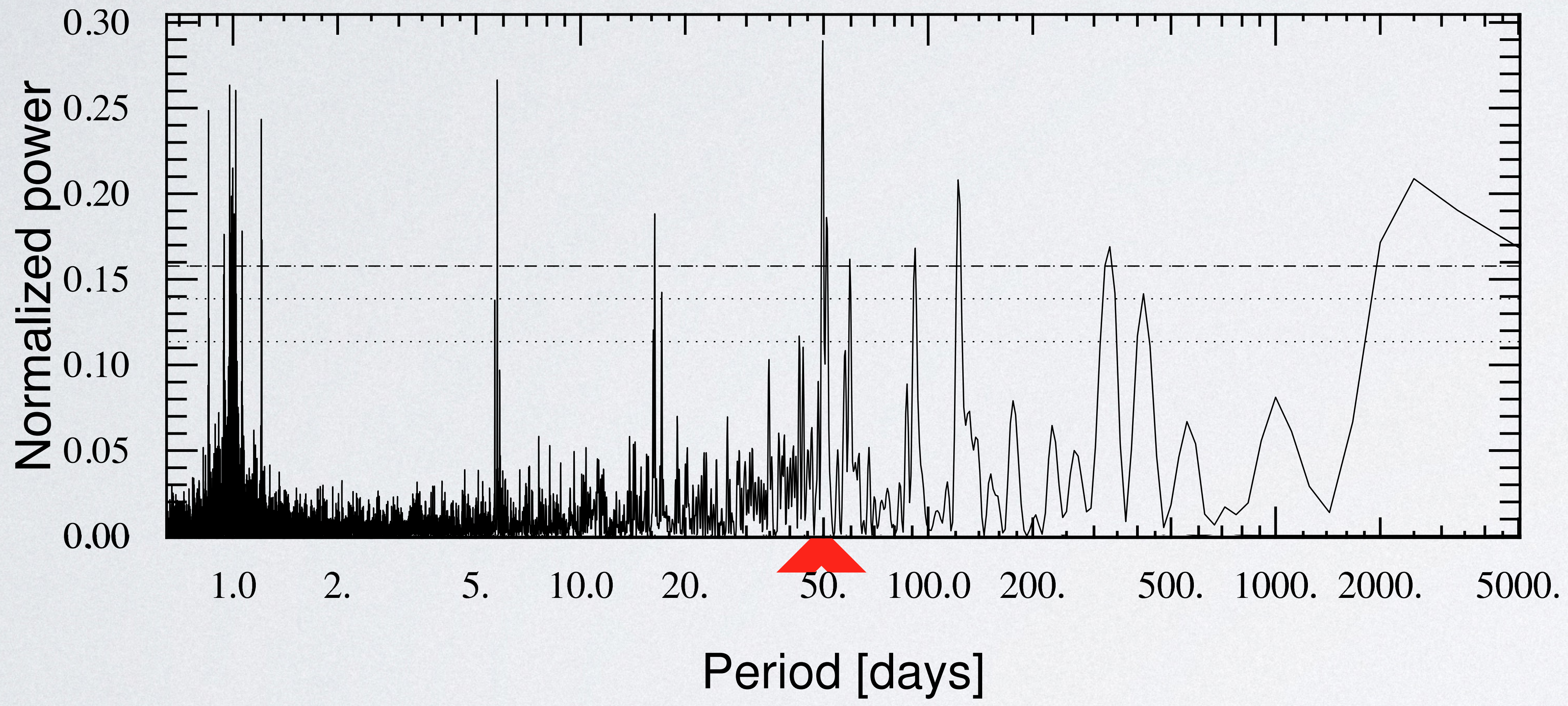
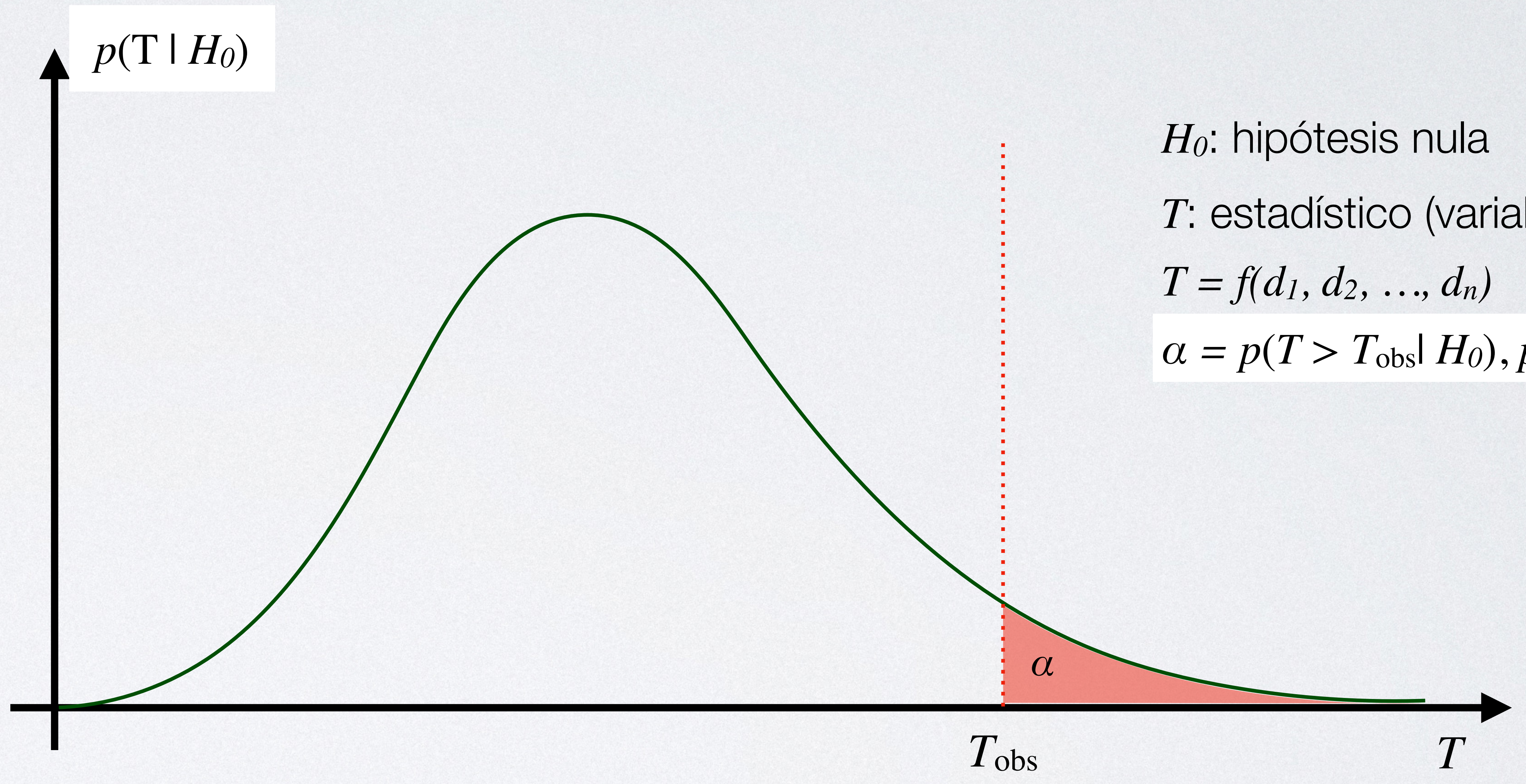
THE GLS PERIODOGRAM

The classical approach to detecting signals in RV time series

Statistical significance evaluated via Null Hypothesis Significance Testing





H_0: hipótesis nula

T: estadístico (variable aleatoria)

$T = f(d_1, d_2, \ldots, d_n)$

$\alpha = p(T > T_{\mathrm{obs}} \mid H_0)$, p-value

Lomb (1976)
Scargle (1982)
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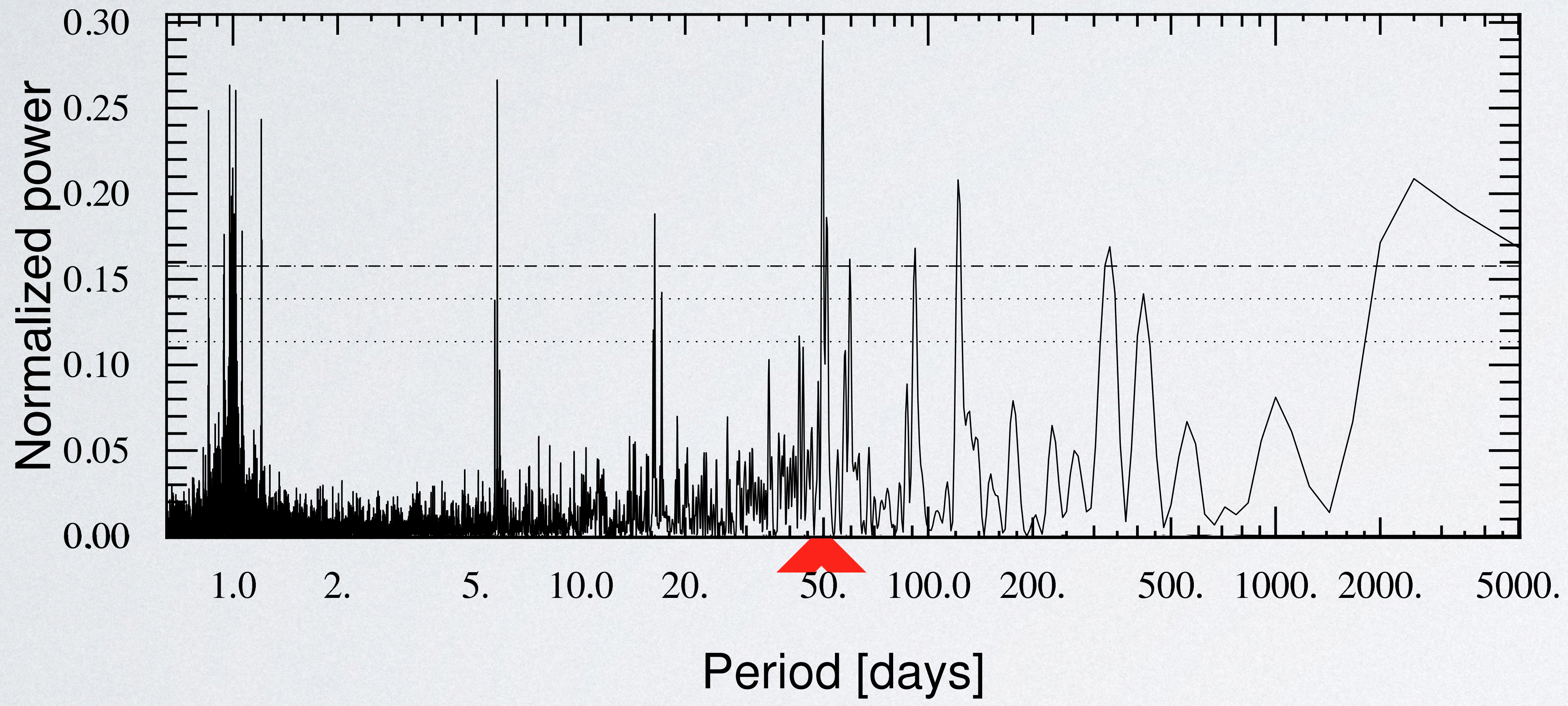
THE GLS PERIODOGRAM

The classical approach to detecting signals in RV time series



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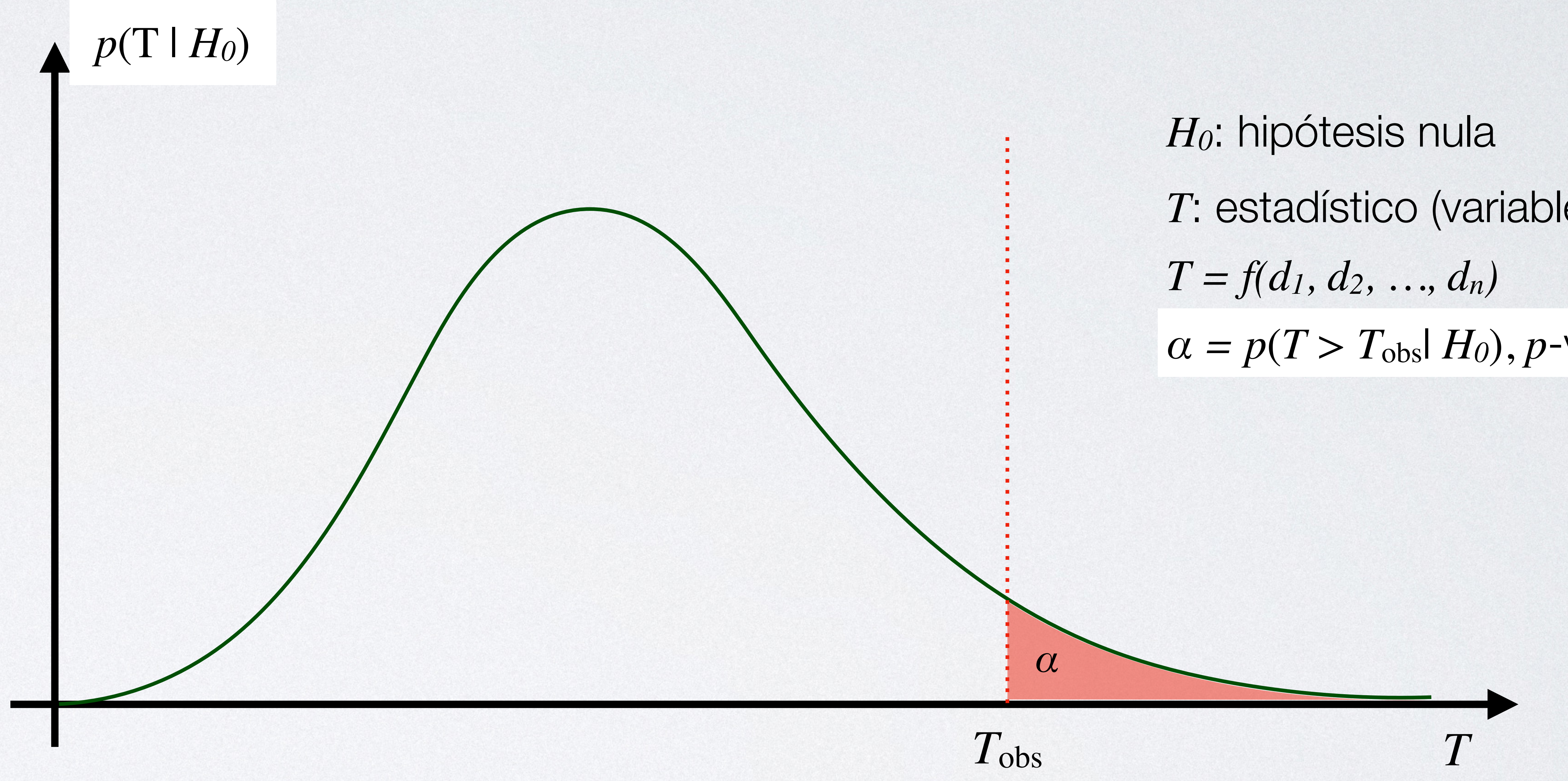

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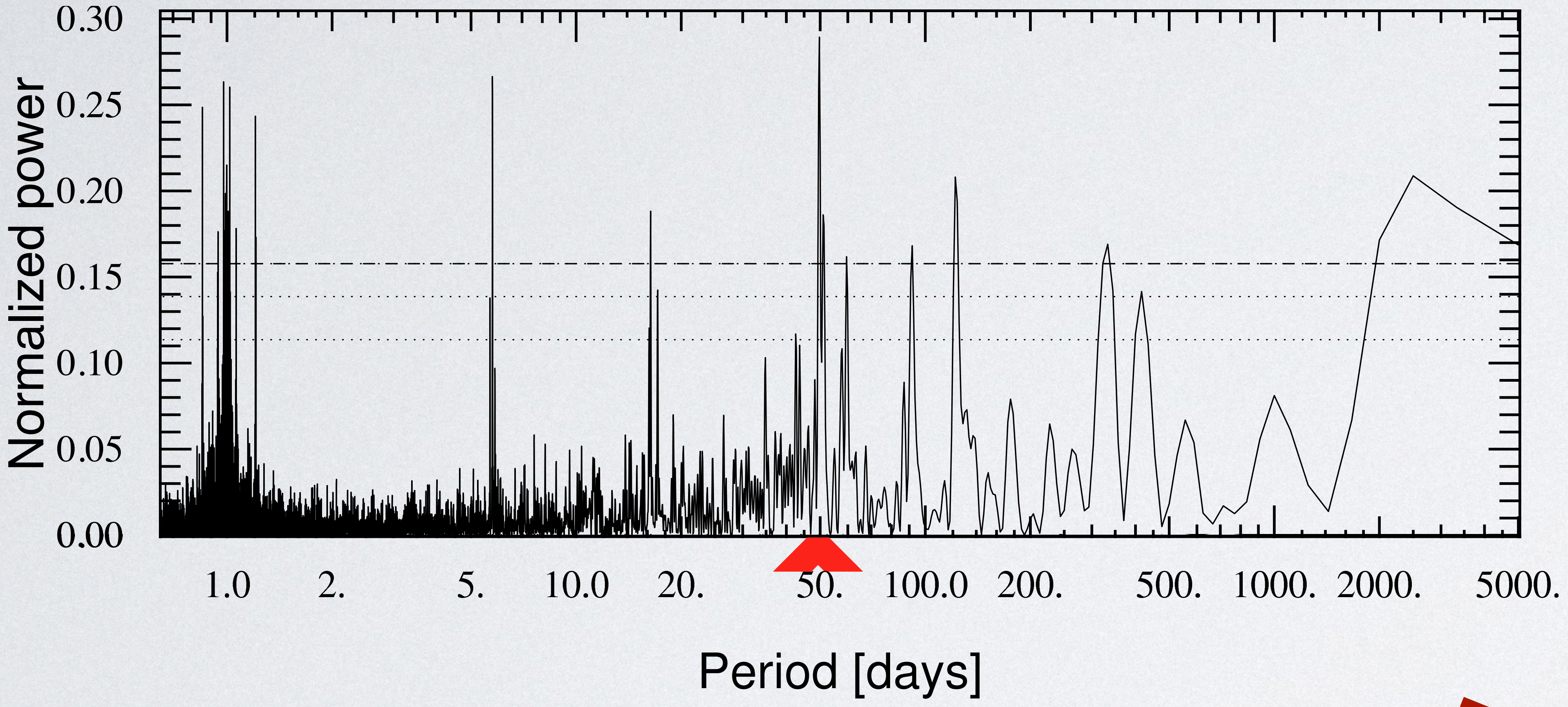
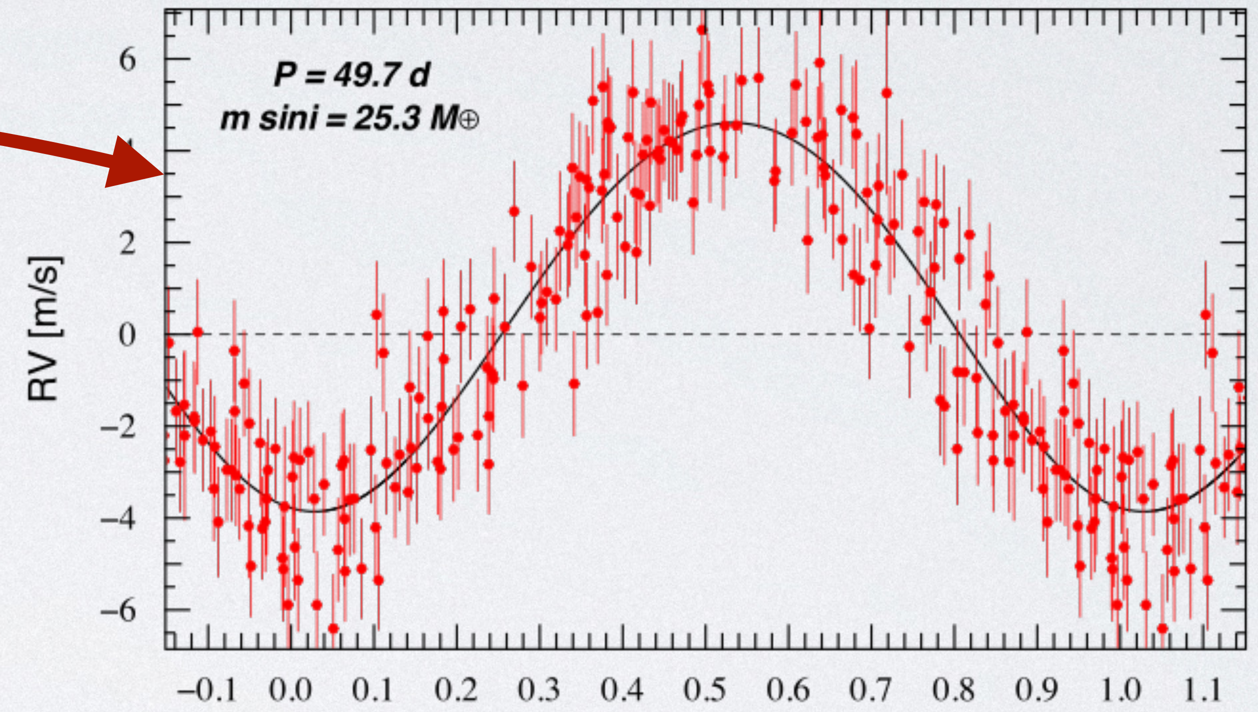
The most commonly used statistics is the power of the largest peak in the periodogram.

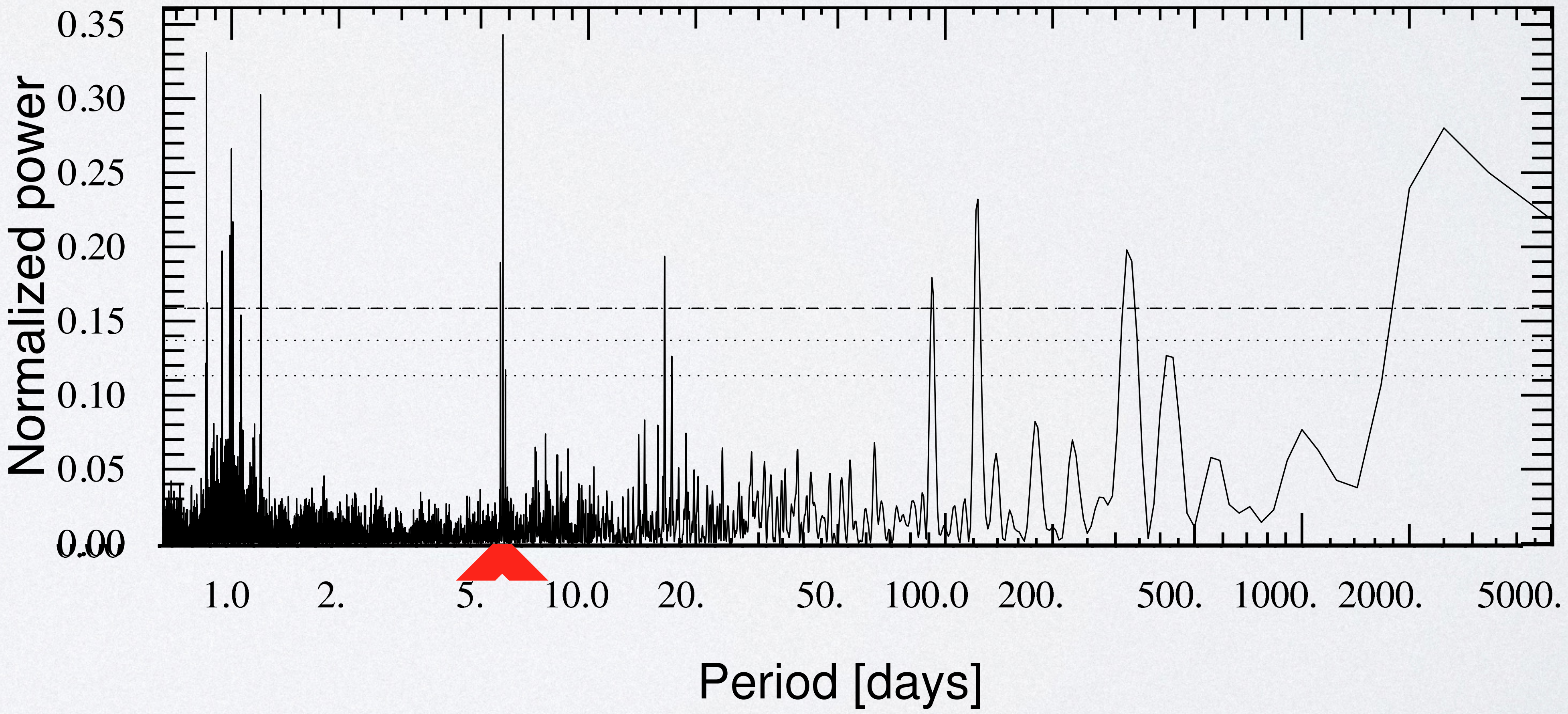
THE GLS PERIODOGRAM

The classical approach to detecting signals in RV time series



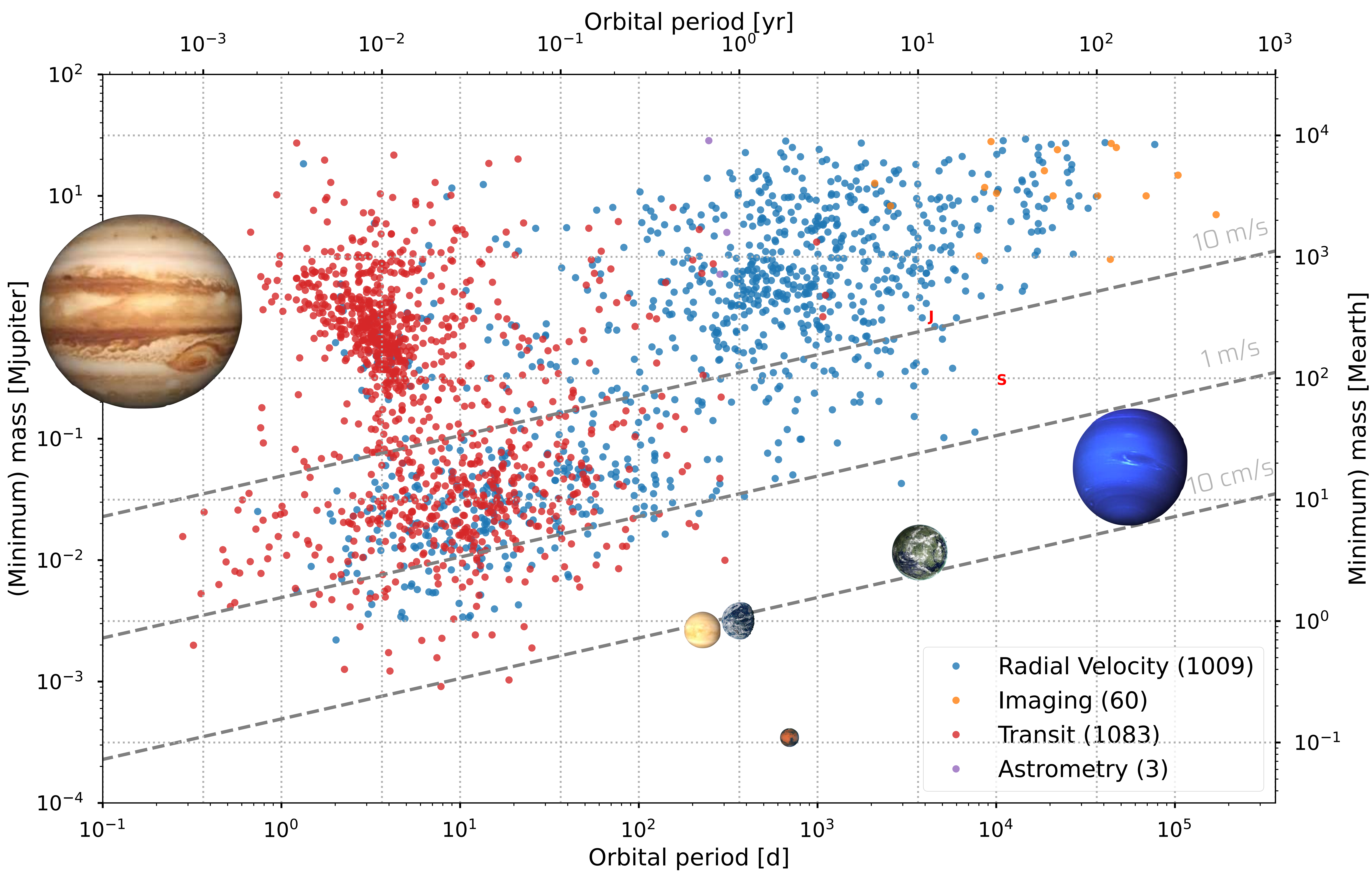
remove





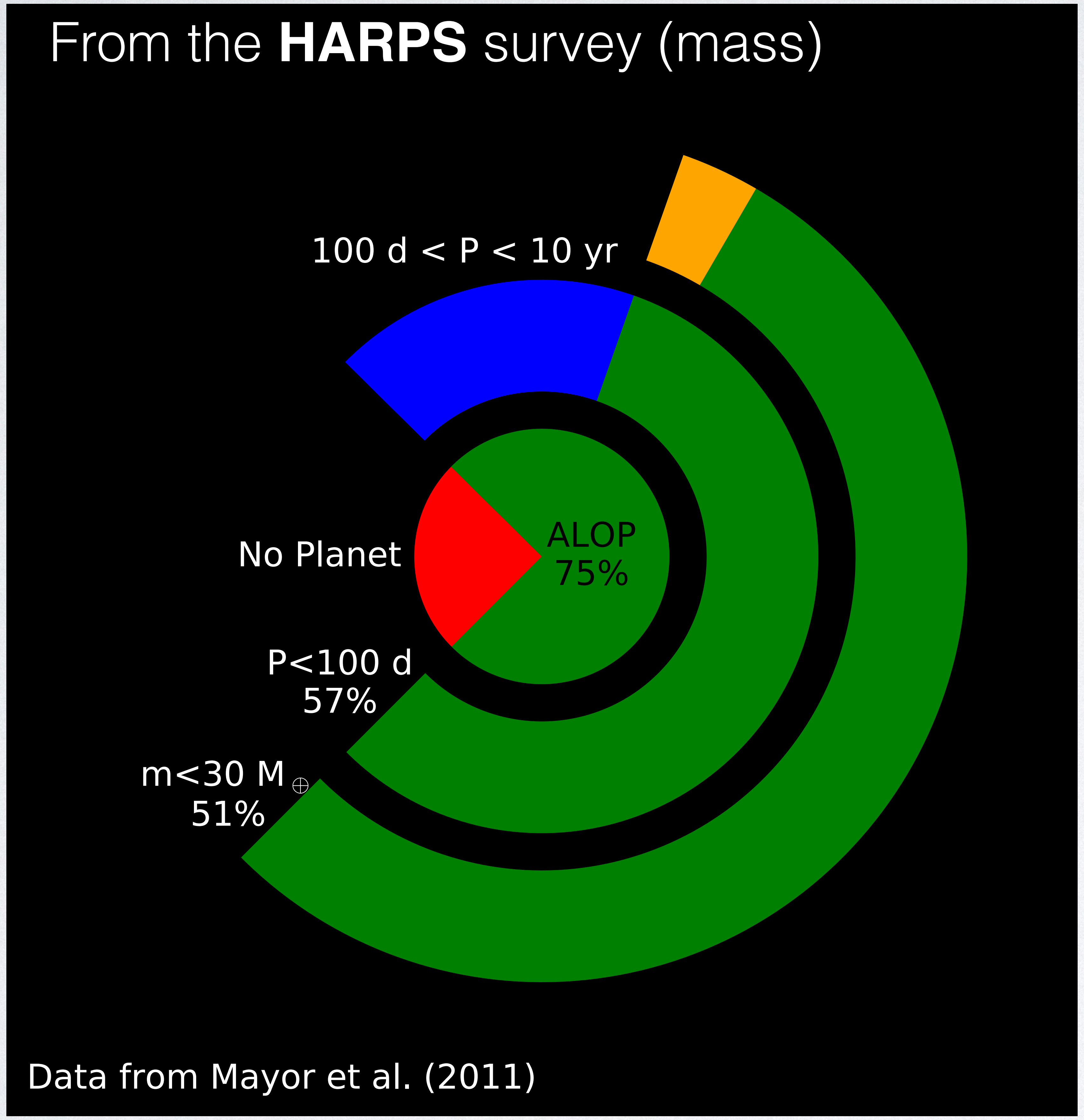
If significant, remove largest peak, which is now considered a real (planet) frequency and continue with the residuals.

Stop when no significant peak is present.

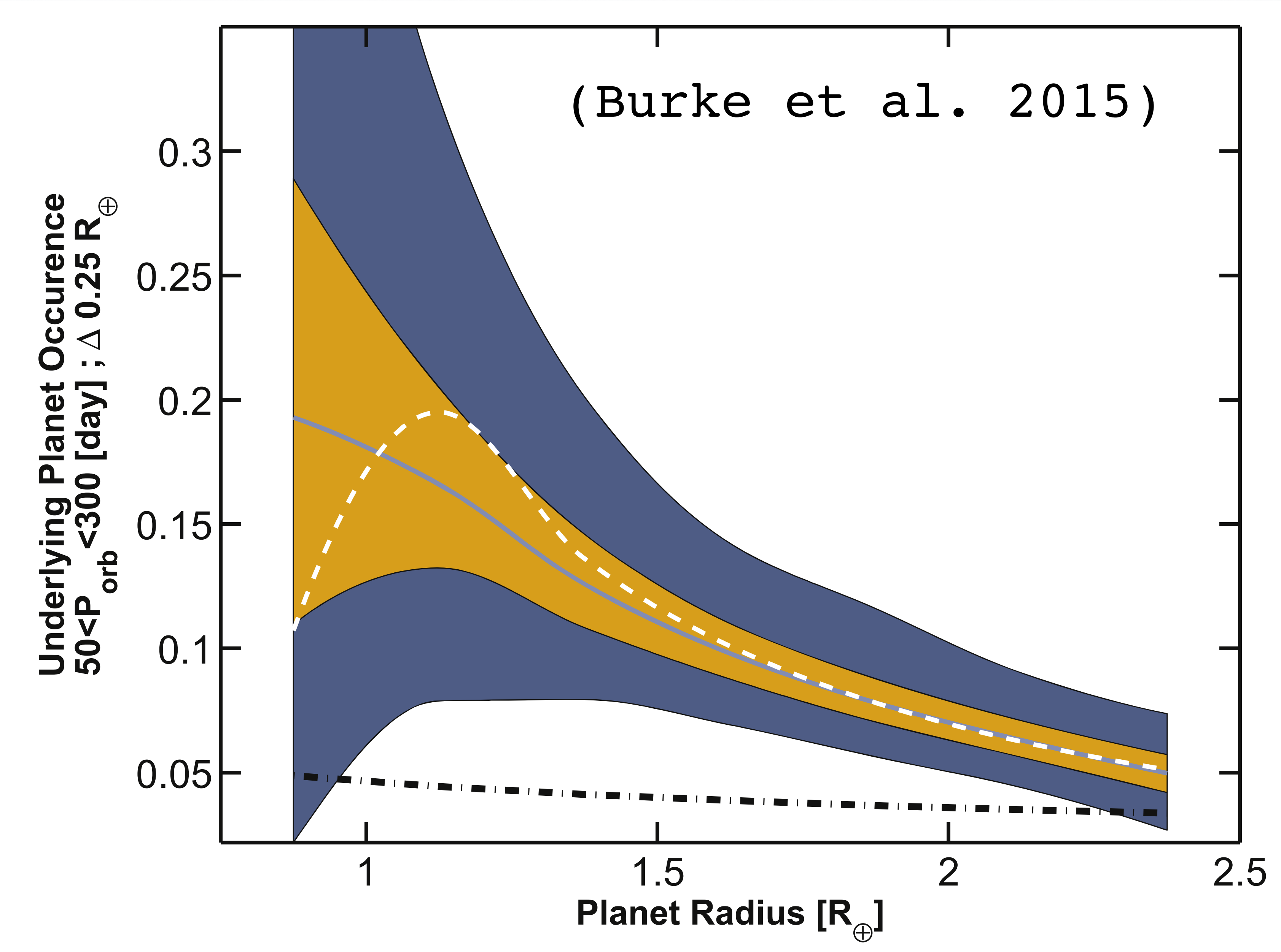


Orbital period [yr]
Orbital period [d]
(Minimum) mass [Mjupiter]
(Minimum) mass [Mearth]
10 m/s
1 m/s
10 cm/s
J
S
Radial Velocity (1009)
Imaging (60)
Transit (1083)
Astrometry (3)

PLANET OCCURRENCE RATES



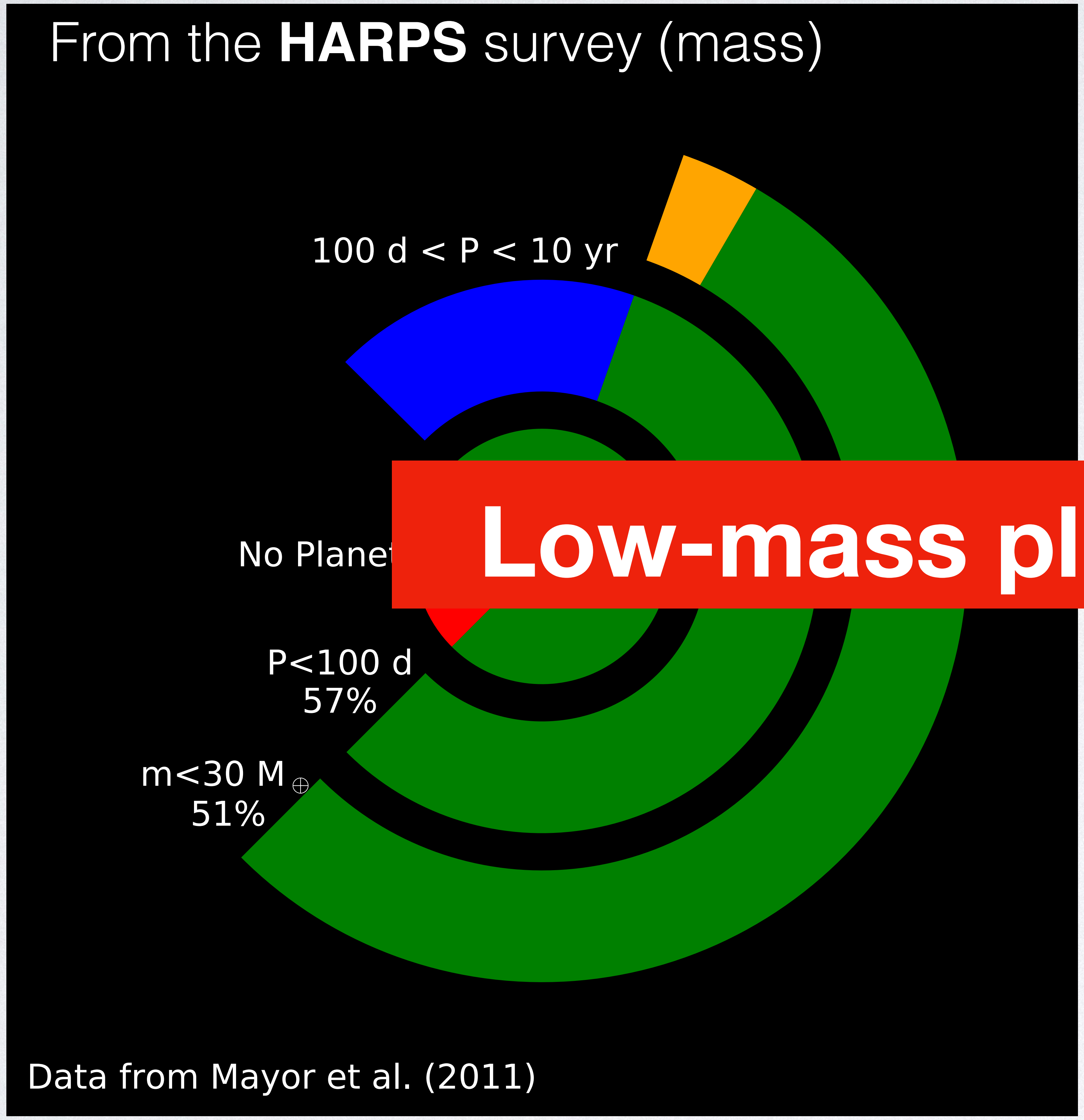
From the **Kepler** mission (radius)



0.77 planets per star [0.49 - 1.3]

See also Youdin (2011), Howard et al. (2012b), Farr et al. (2014), among others

PLANET OCCURRENCE RATES



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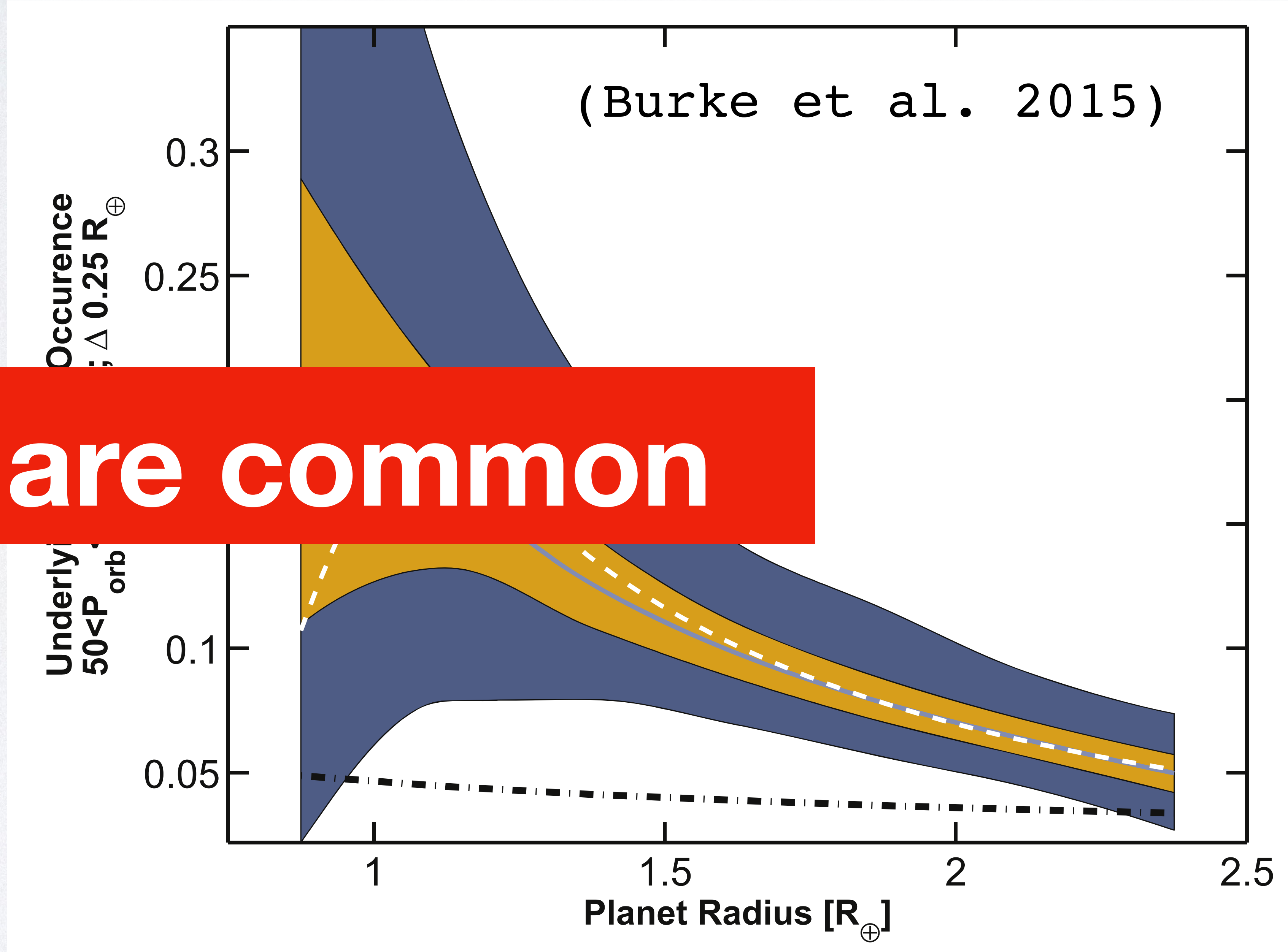
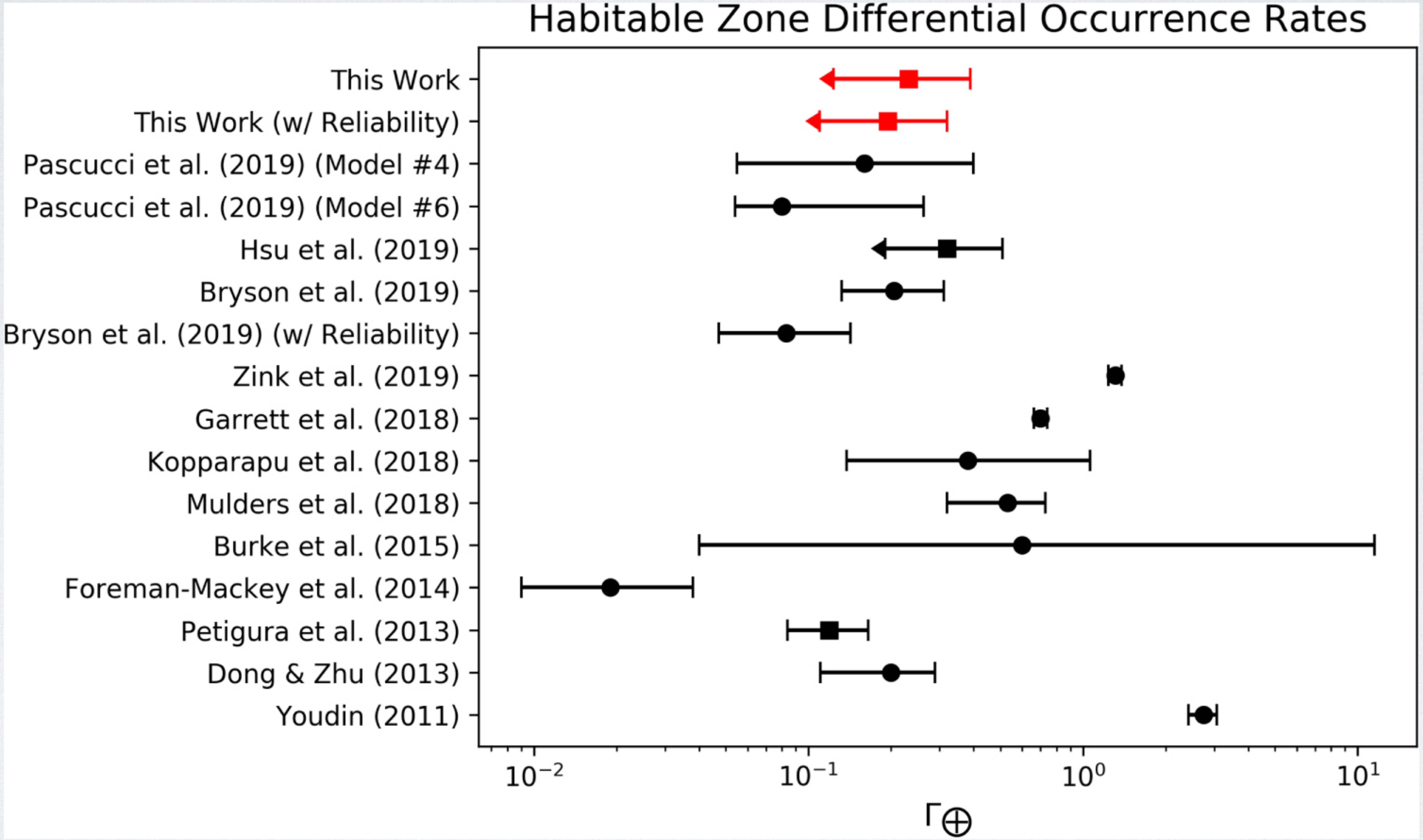


Low-mass planets are common

0.77 planets per star [0.49 - 1.3]

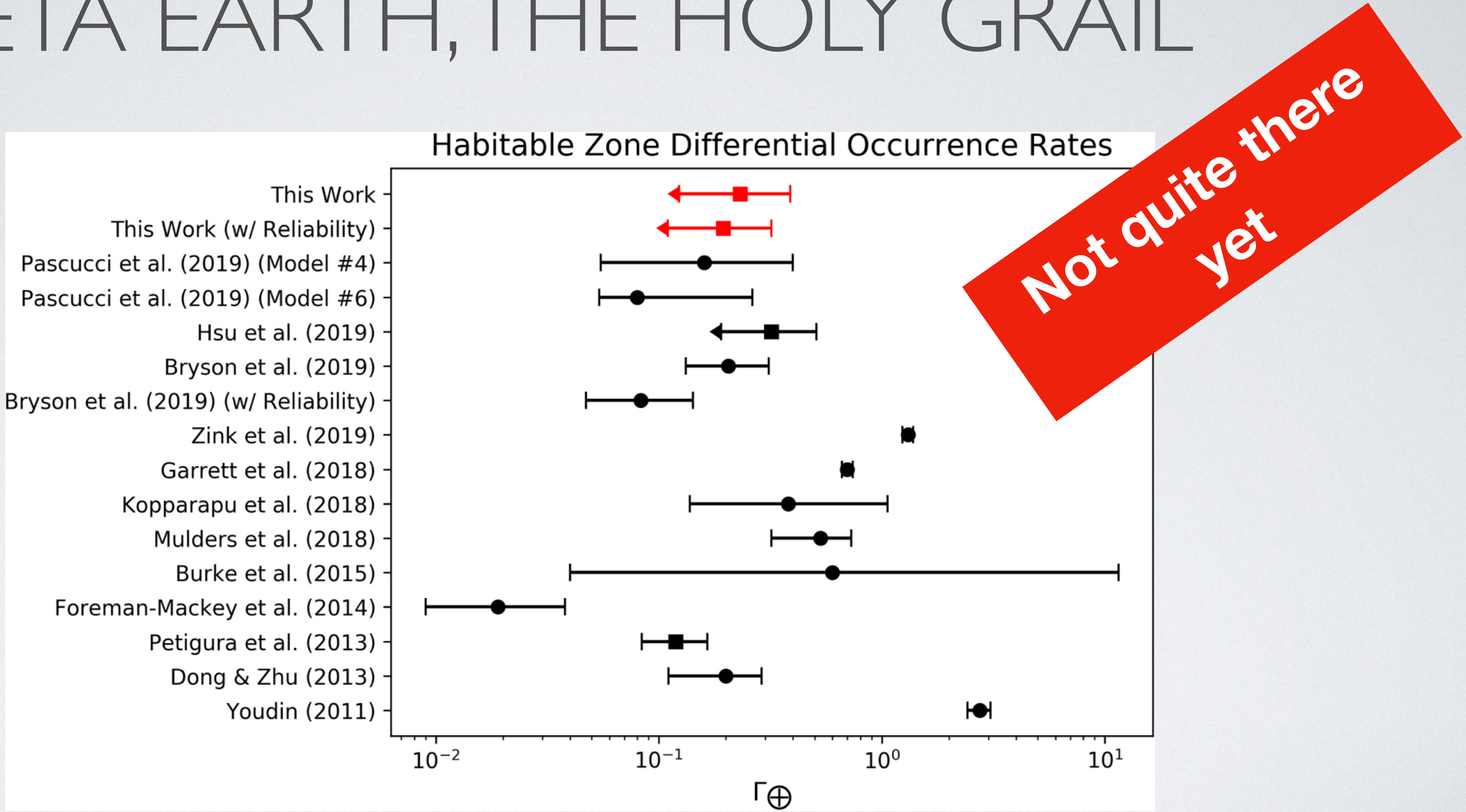
See also Youdin (2011), Howard et al. (2012b), Farr et al. (2014), among others

ETA EARTH, THE HOLY GRAIL

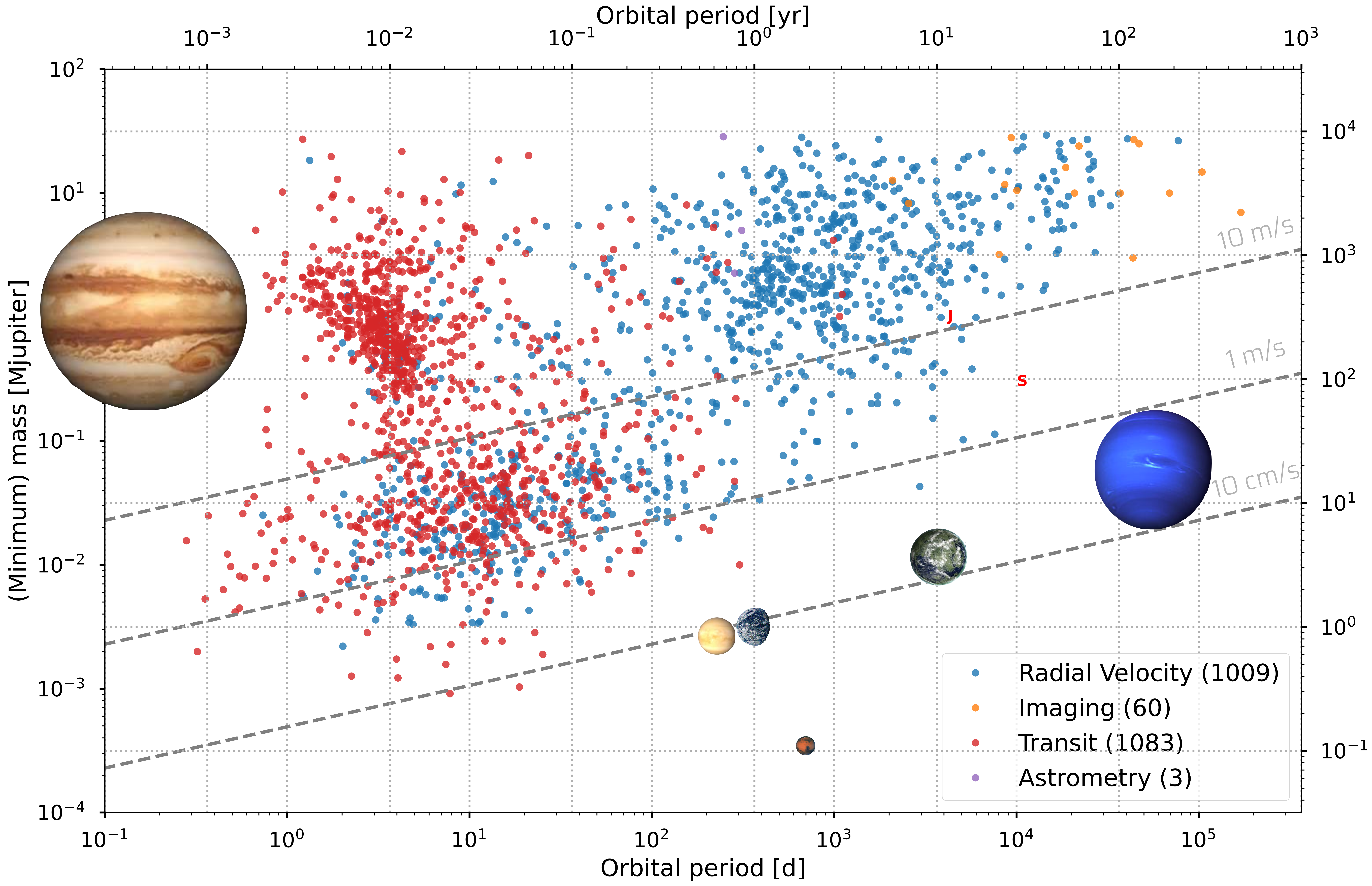


Kunimoto & Matthews (2020)

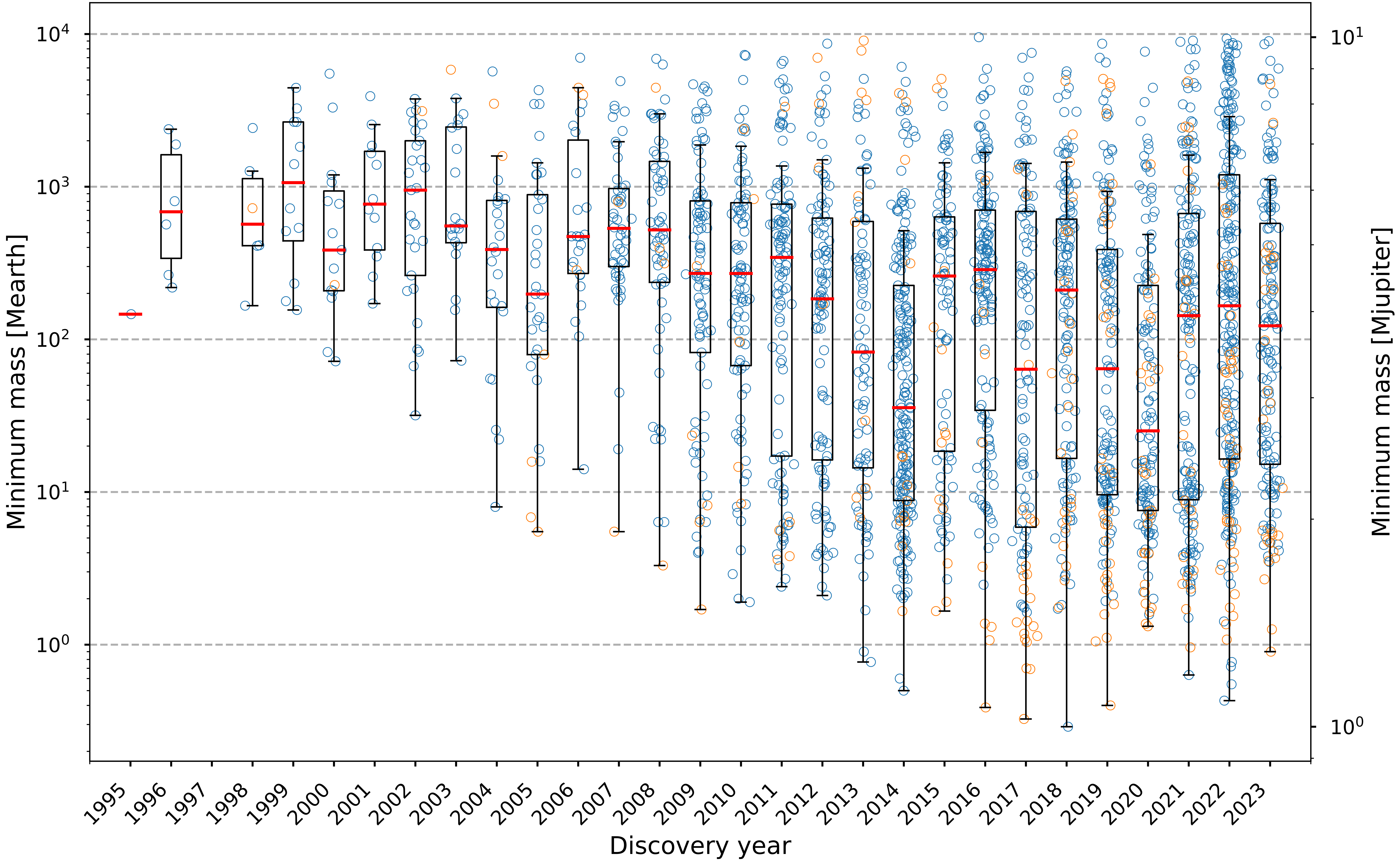
ETA EARTH, THE HOLY GRAIL



Kunimoto & Matthews (2020)



Orbital period [yr]
10^{-3} 10^{-2} 10^{-1} 10^{0} 10^{1} 10^{2} 10^{3}
(Minimum) mass [Mjupiter]
10^{2} 10^{1} 10^{-1} 10^{-2} 10^{-3} 10^{-4}
(Minimum) mass [Mearth]
10^{4} 10^{3} 10^{2} 10^{1} 10^{0} 10^{-1}
Orbital period [d]
10^{-1} 10^{0} 10^{1} 10^{2} 10^{3} 10^{4} 10^{5}
10 m/s
1 m/s
10 cm/s
J
S
Radial Velocity (1009)
Imaging (60)
Transit (1083)
Astrometry (3)



Minimum mass [Mearth]
Minimum mass [Mjupiter]
Discovery year
10^{4}
10^{3}
10^{2}
10^{1}
10^{0}
10^{1}
10^{0}
1995
1996
1997
1998
1999
2000
2001
2002
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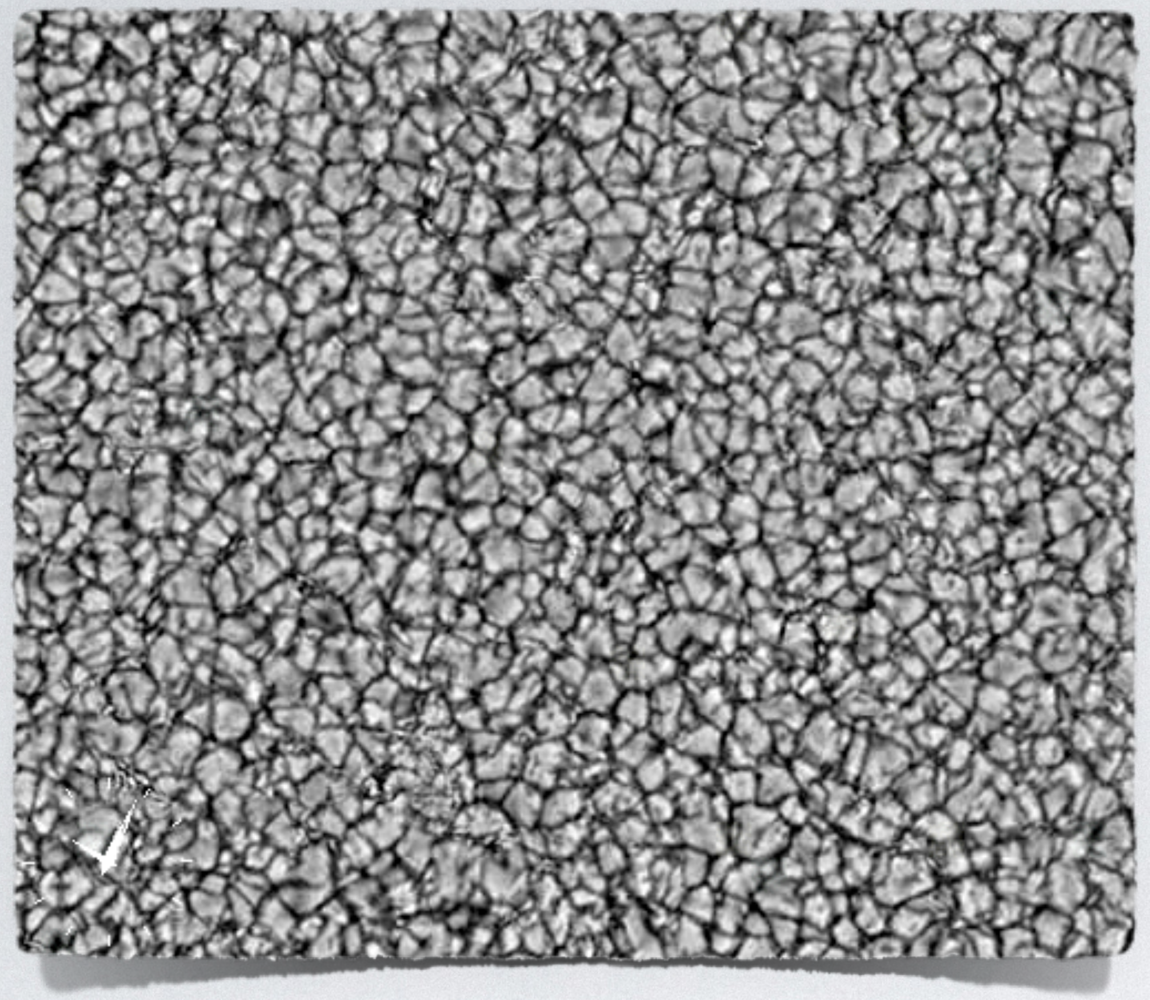
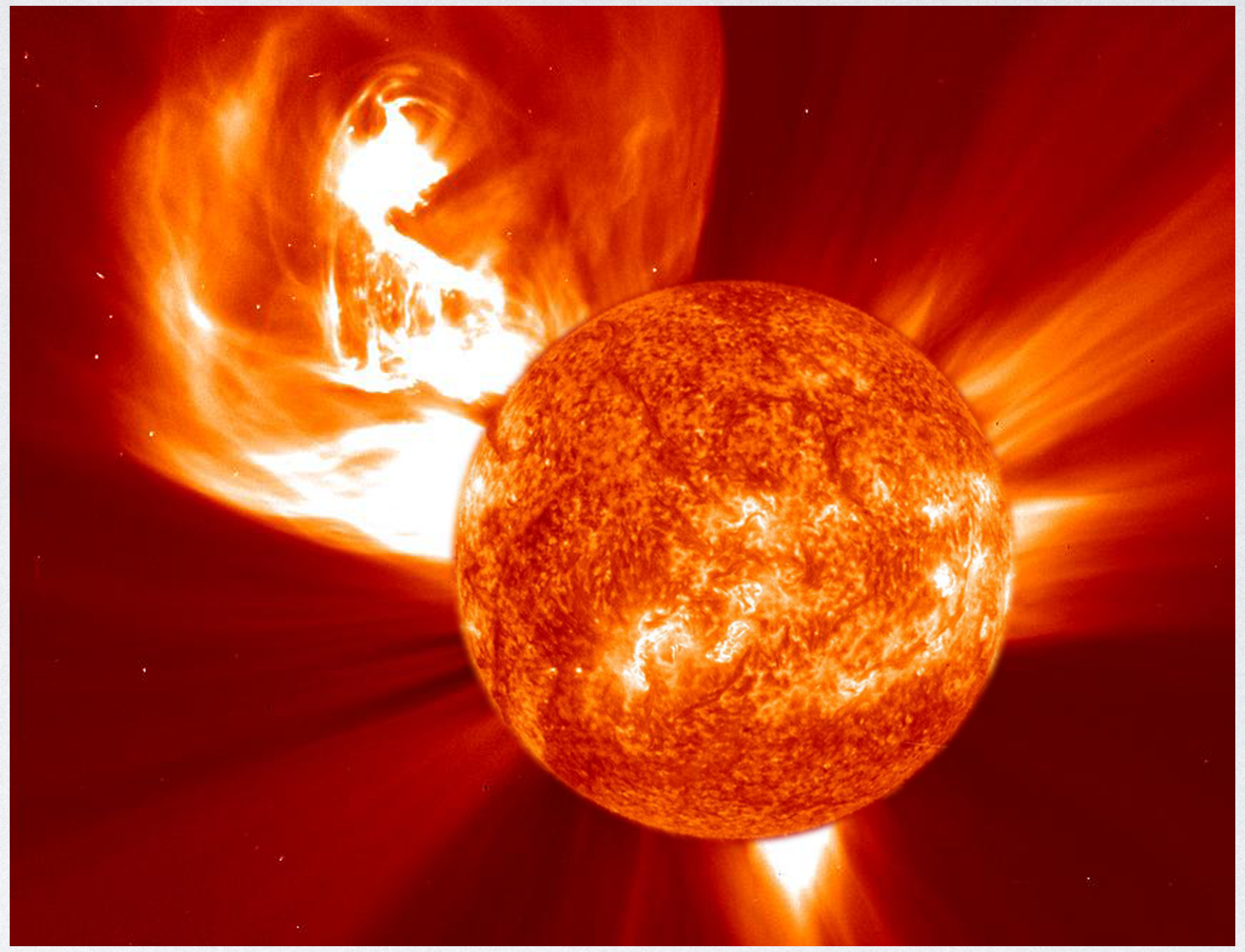
2022
2023

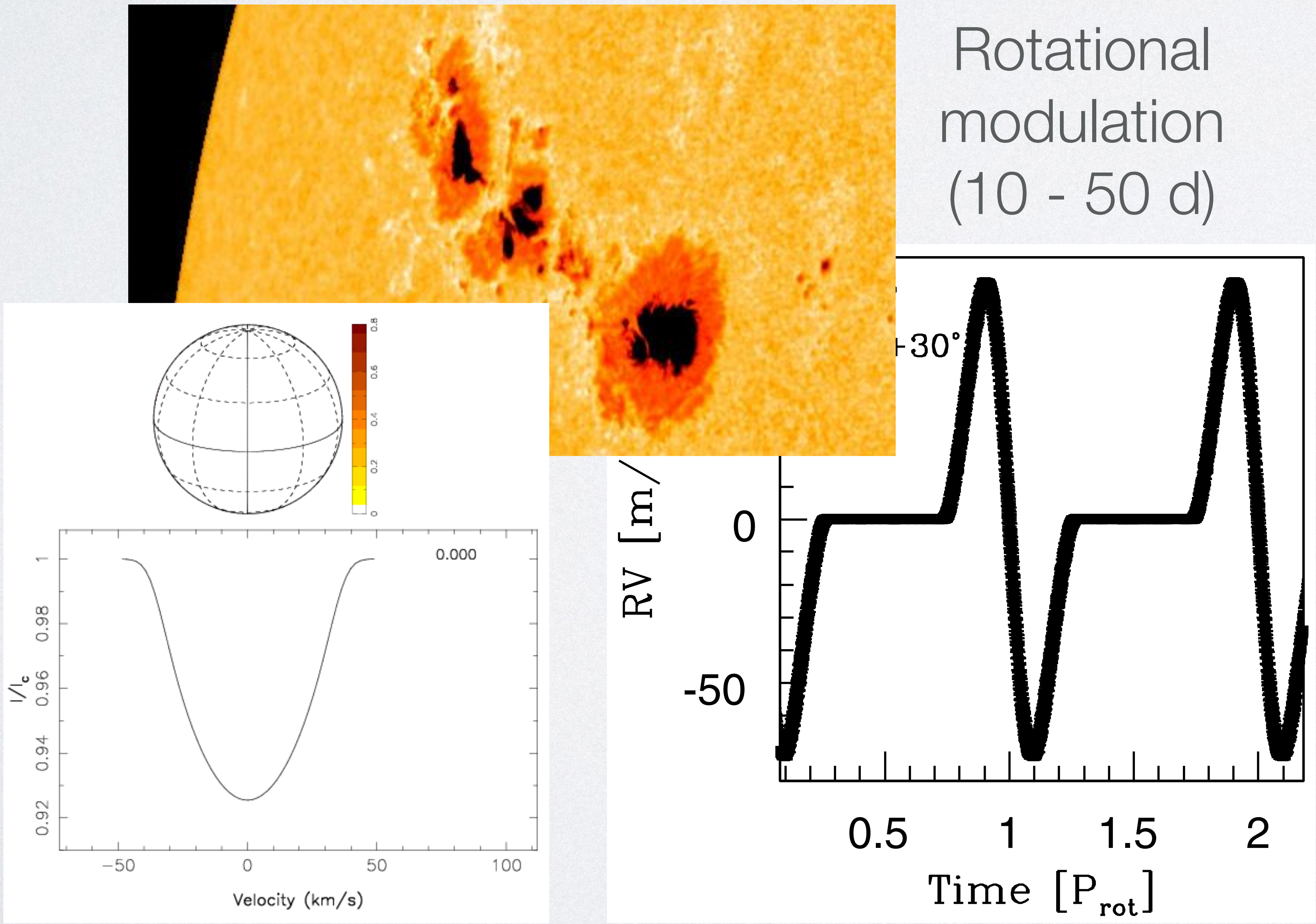
THE MANY FACES OF STELLAR ACTIVITY



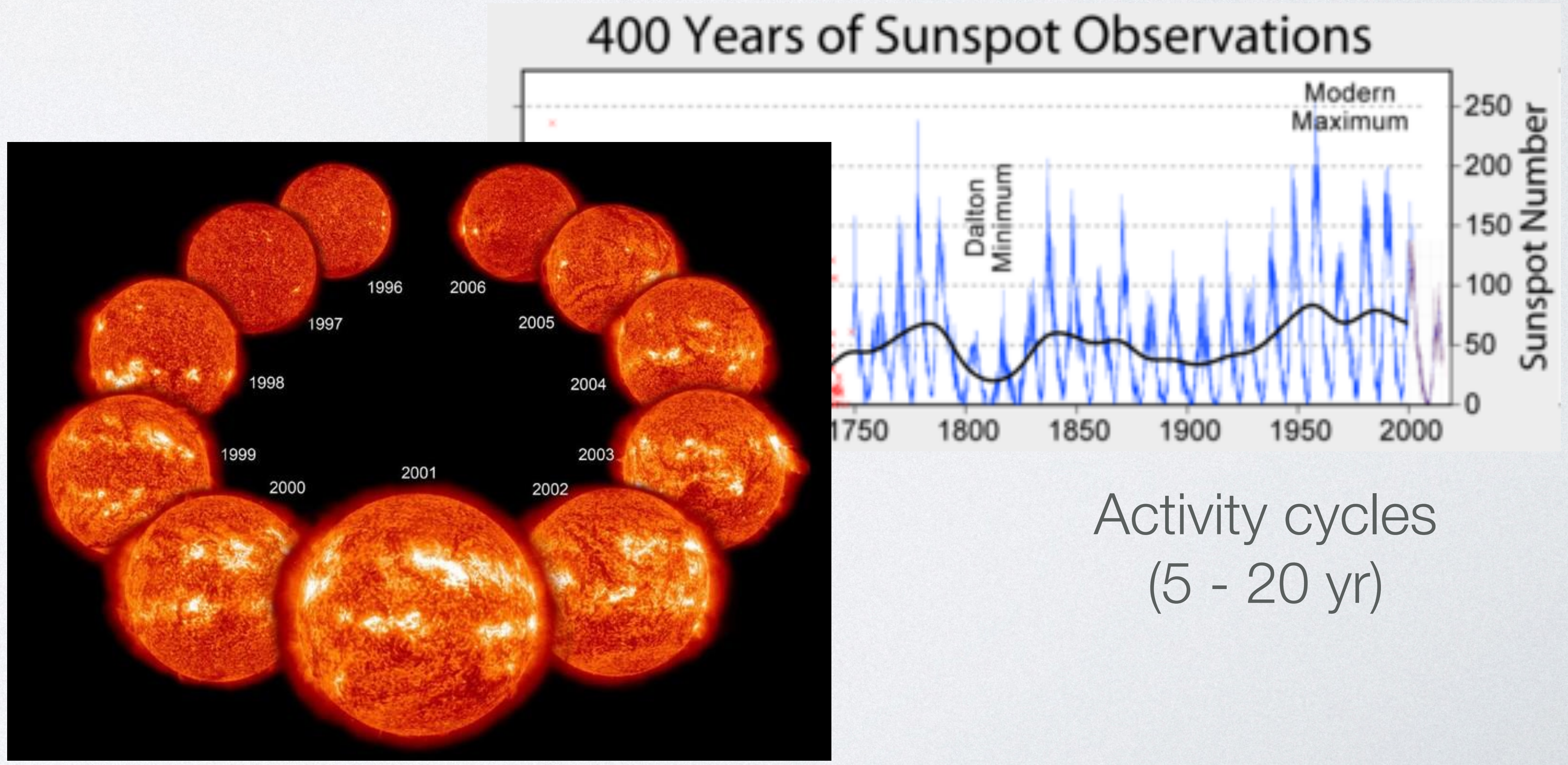
Granulation
(15 m - 2 d)



Flares & CMEs
(~ 1 h)

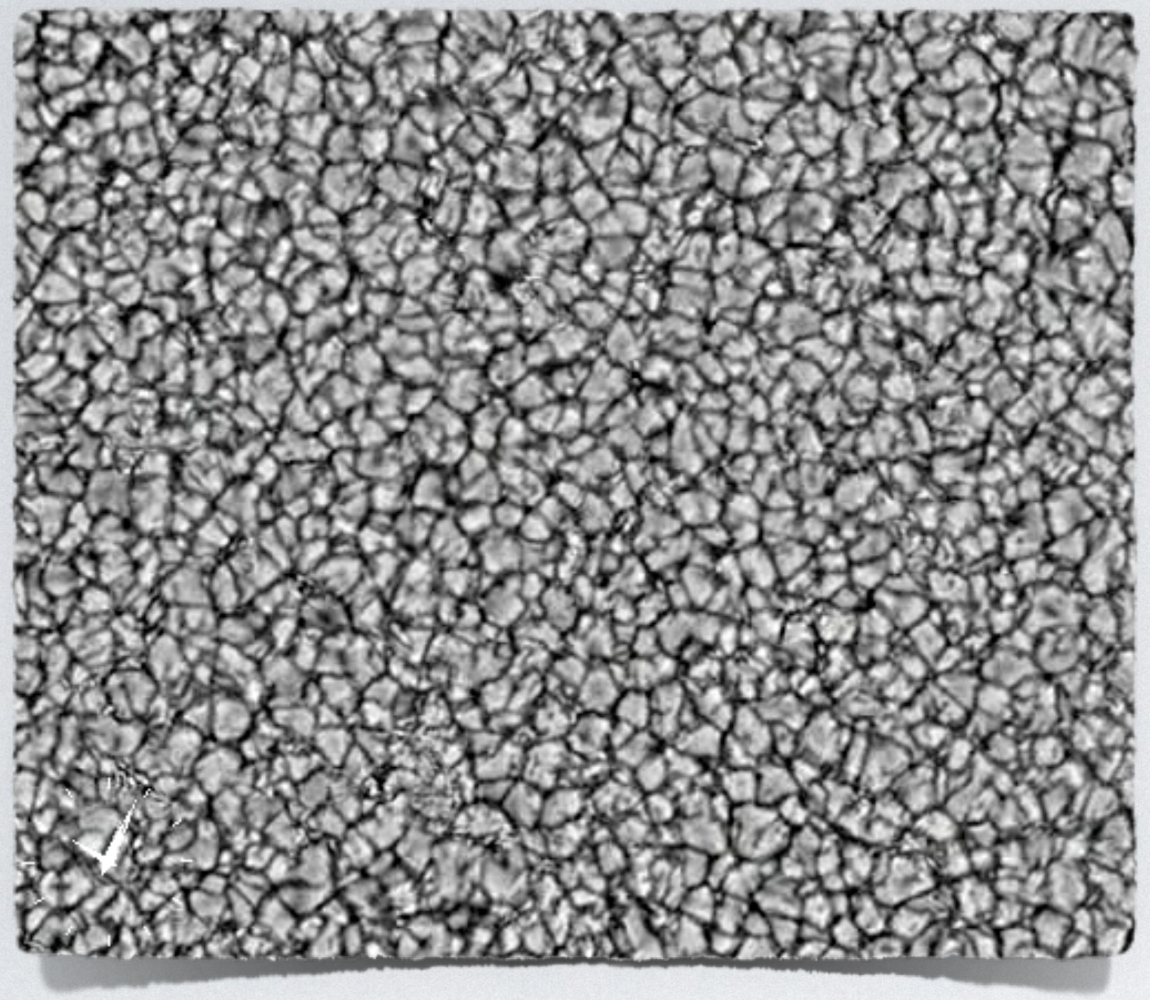


Rotational
modulation
(10 - 50 d)



Activity cycles
(5 - 20 yr)

THE MANY FACES OF STELLAR ACTIVITY



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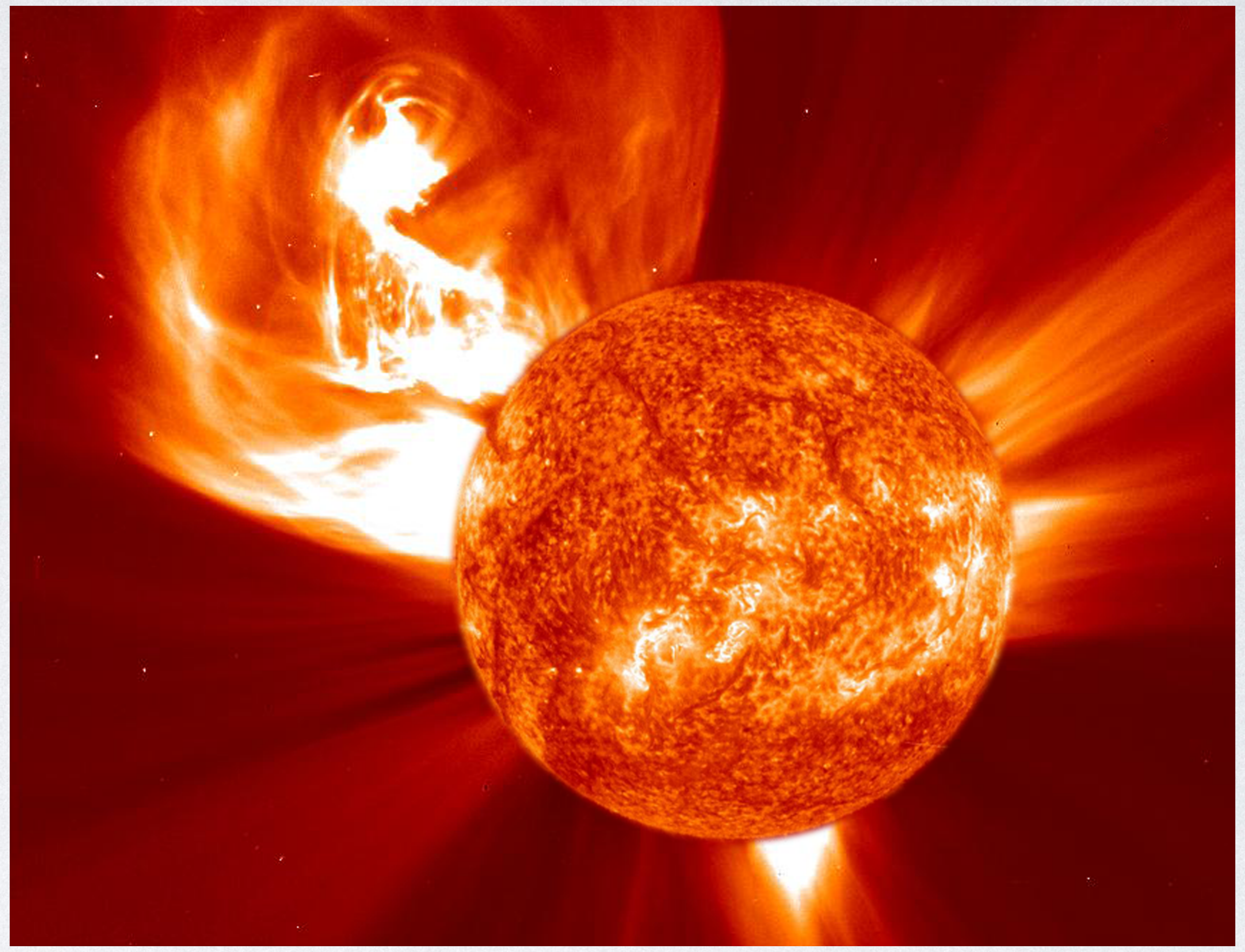

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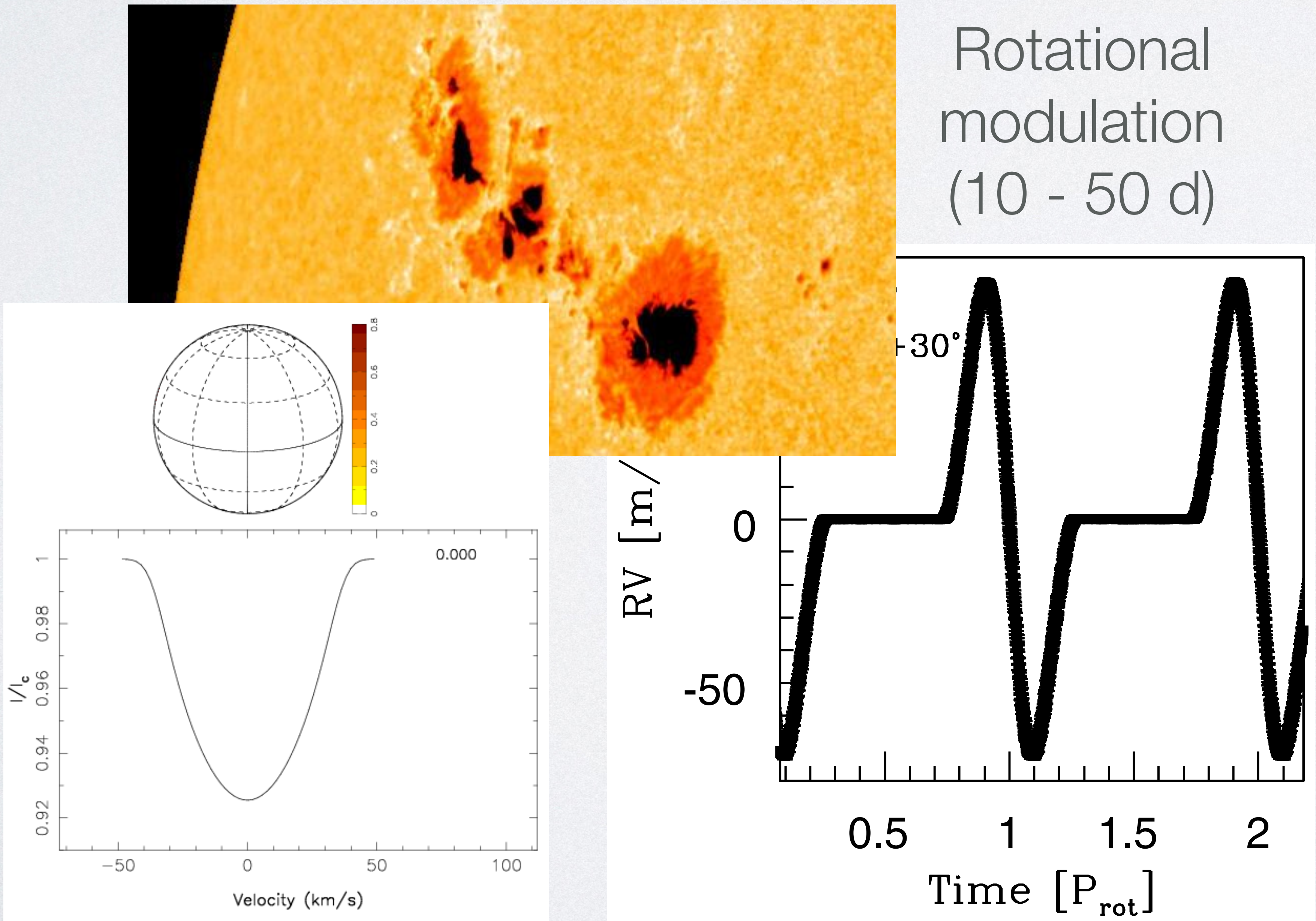
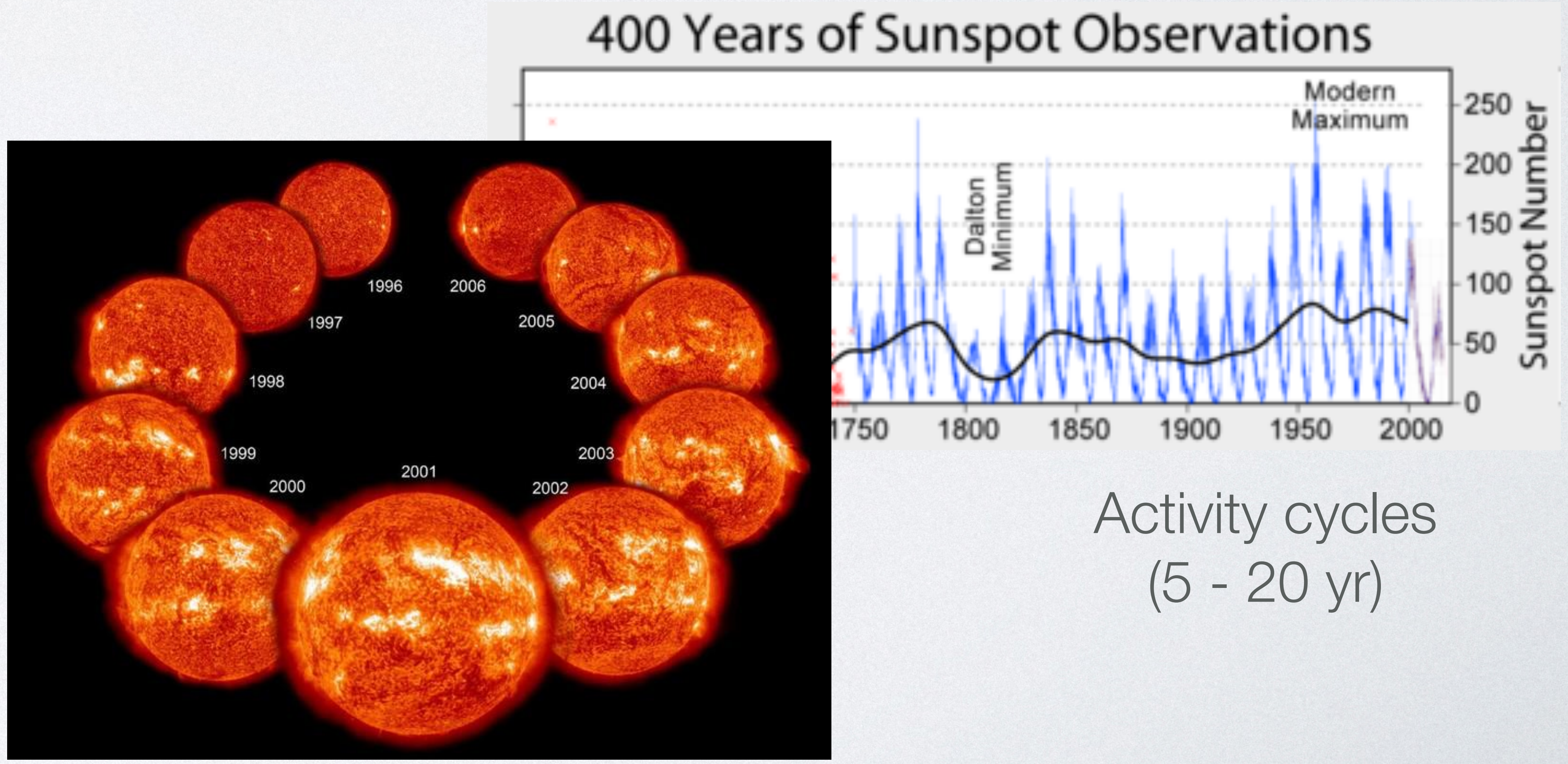


Rotational
modulation
(10 - 50 d)

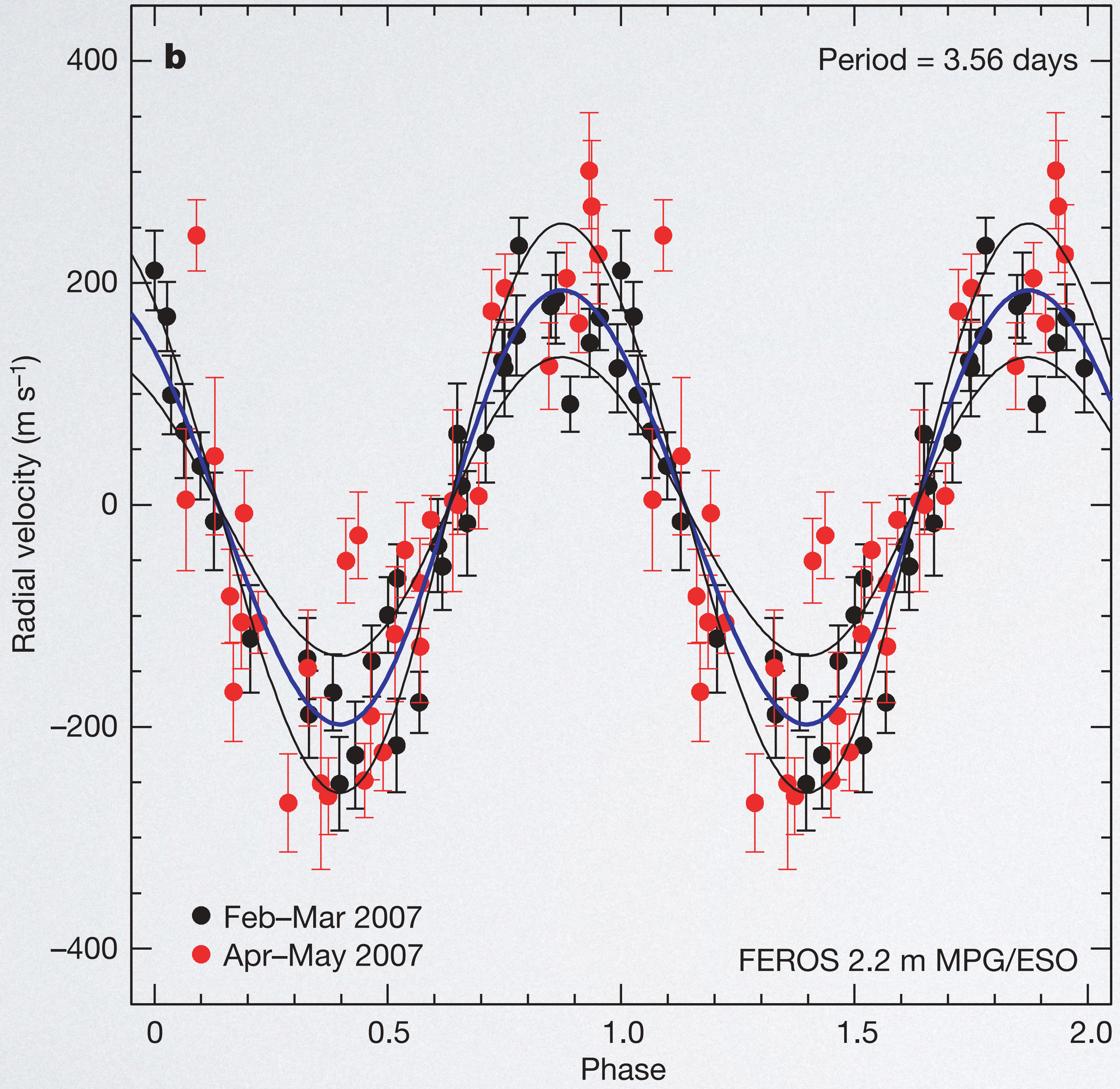


Activity cycles
(5 - 20 yr)

FALSE DETECTIONS

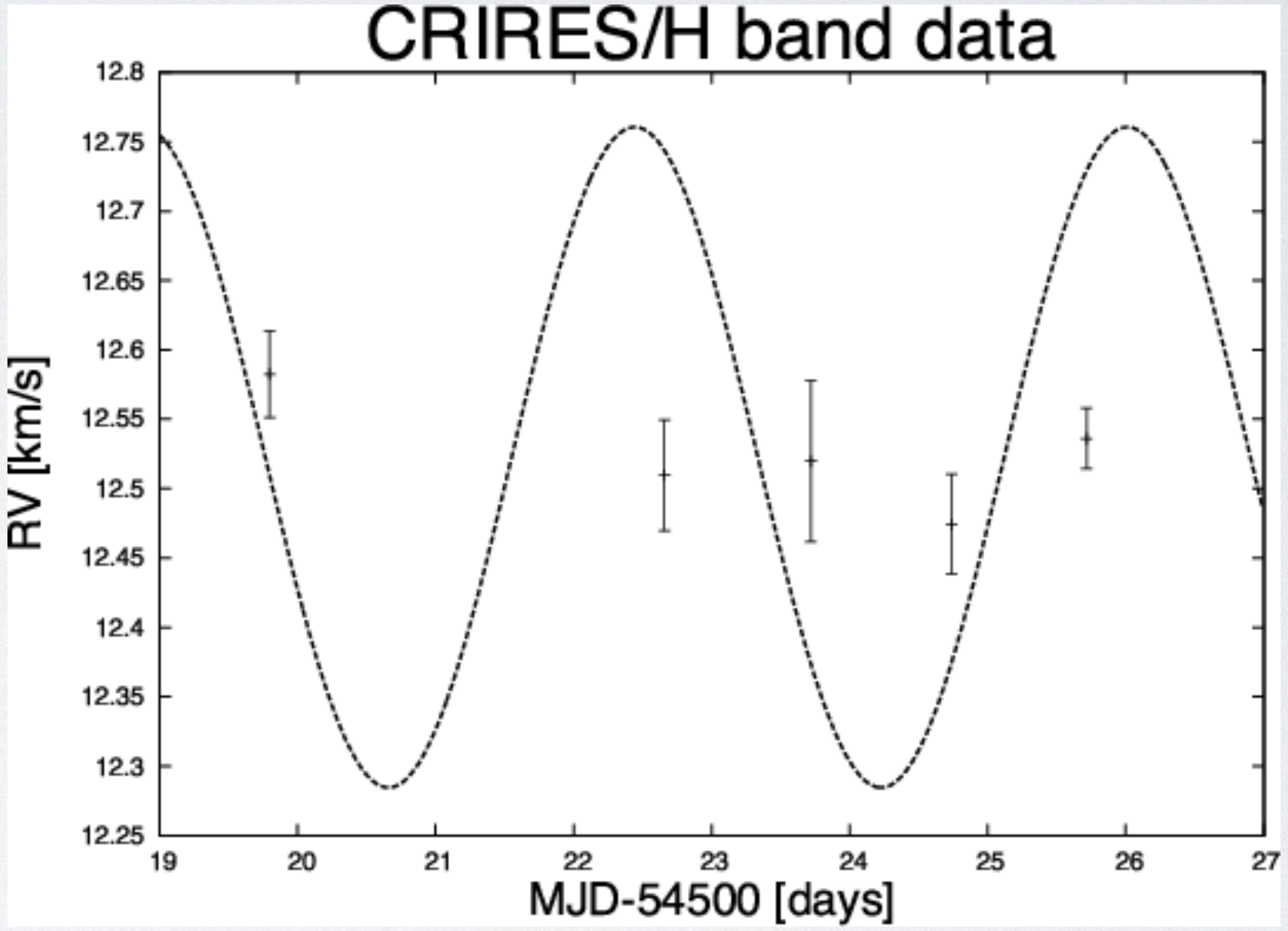
TW Hya has only 8-10 Myr of age.

RV consistent over 3 months



Setiawan et al. (2008)

Variations inconsistent through different bandpasses



Huélamo et al. (2008)

A long-lived active region producing coherent RV effect over months.

NOISE MODELS

Astronomy & Astrophysics manuscript no. RV_challenge_paper_II_v4 ©ESO 2018
October 16, 2018

Radial-Velocity Fitting Challenge ★

II. First results of the analysis of the data set

X. Dumusque[1,2] ★★, F. Borsa[3], M. Damasso[4], R. Díaz[1], P. C. Gregory[5], N.C. Hara[6], A. Hatzes[7], V. Rajpaul[8], M. Tuomi[9], S. Aigrain[8], G. Anglada-Escudé[9,10], A.S. Bonomo[4], G. Boué[6], F. Dauvergne[6], G. Frustagli[3], P. Giacobbe[4], R. D. Haywood[2], H. R. A. Jones[9], M. Pinamonti[11,12], E. Poretti[3], M. Rainer[3], D. Ségransan[1], A. Sozzetti[4], and S. Udry[1]

$$\mathbf{v} = f(\boldsymbol{x}|\boldsymbol{\theta}) + \epsilon$$

$$\epsilon \sim N(0, \sigma^2)$$

"The most efficient methods to recover planetary signals take into account the different activity indicators, use **red-noise models** to account for stellar RV signals and a **Bayesian framework** to provide model comparison in a robust statistical approach."

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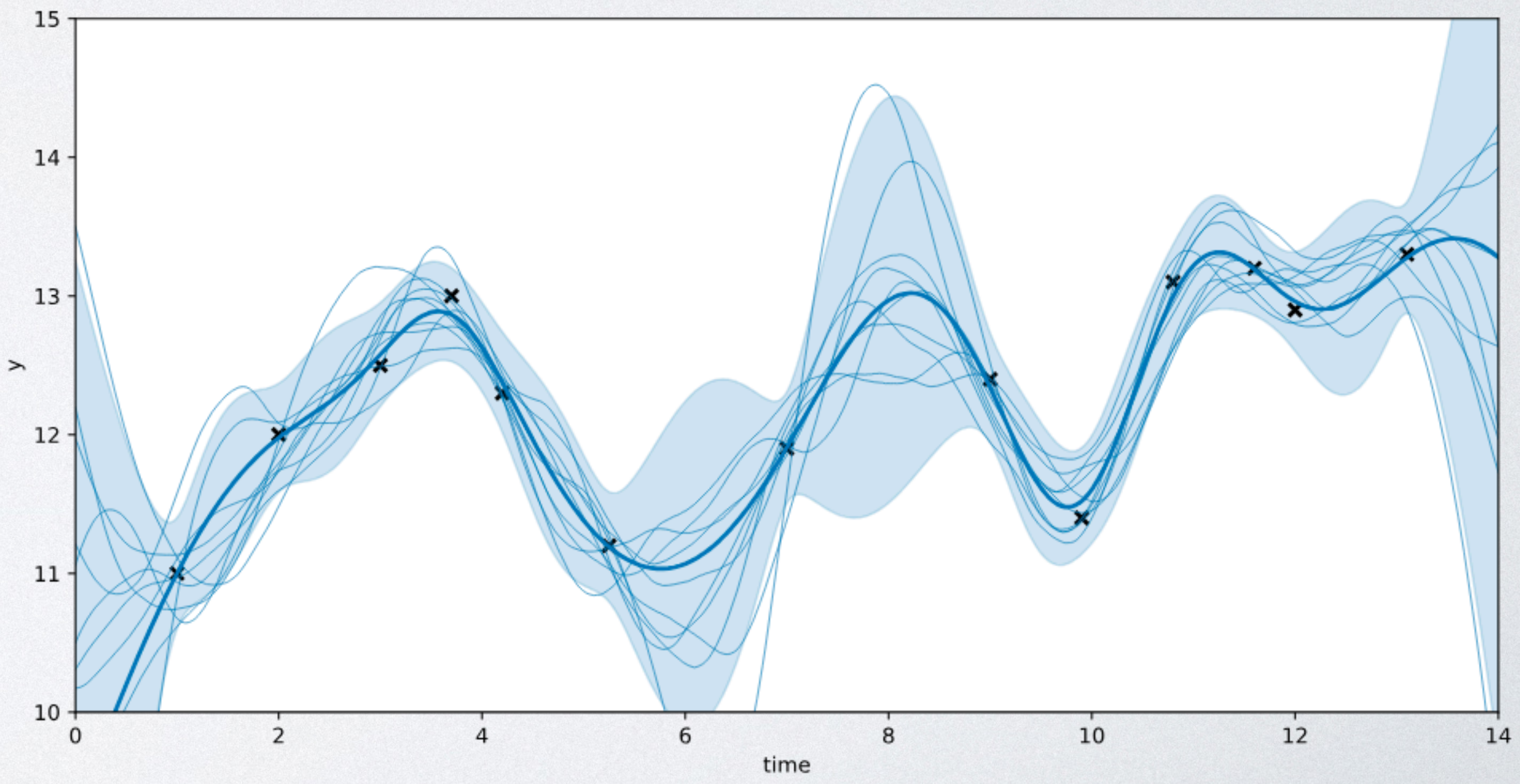
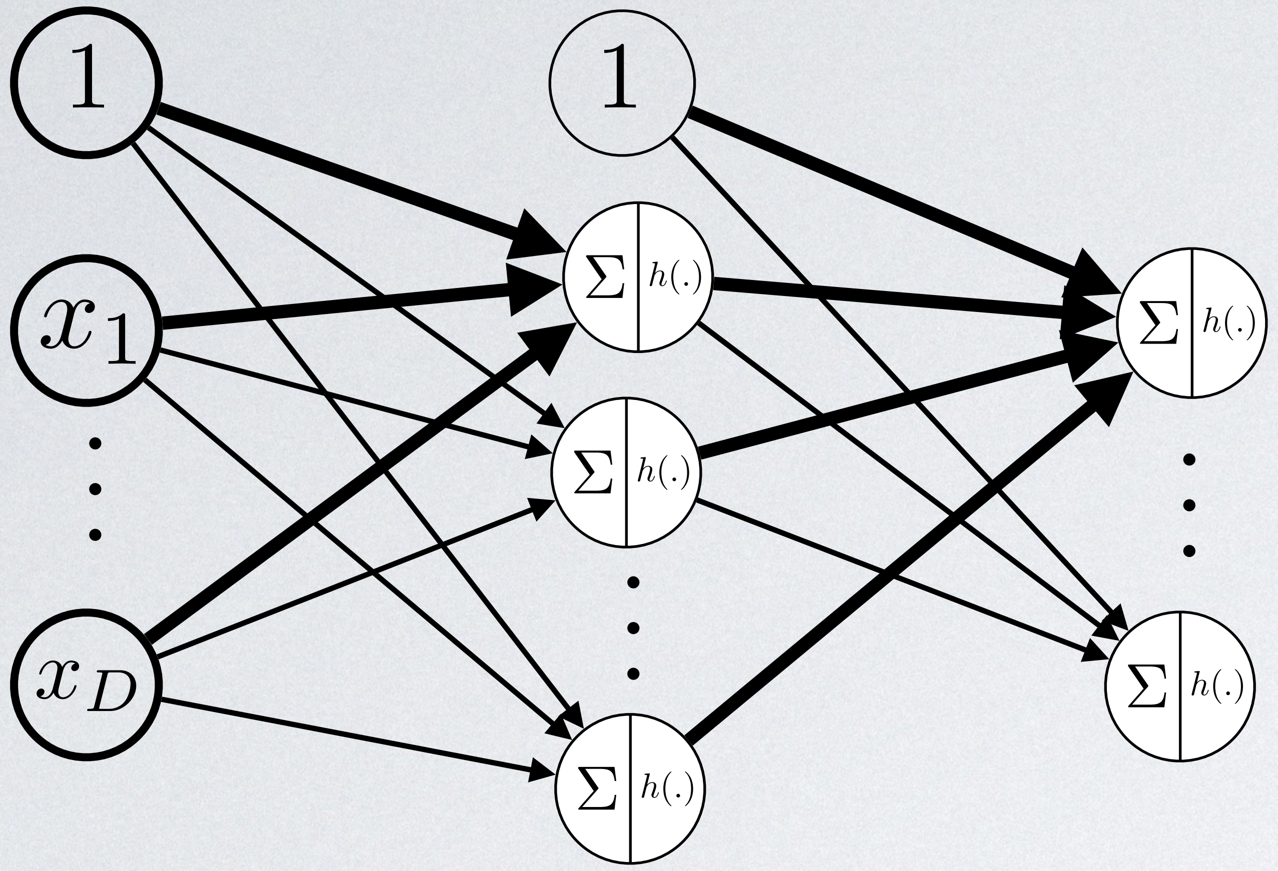


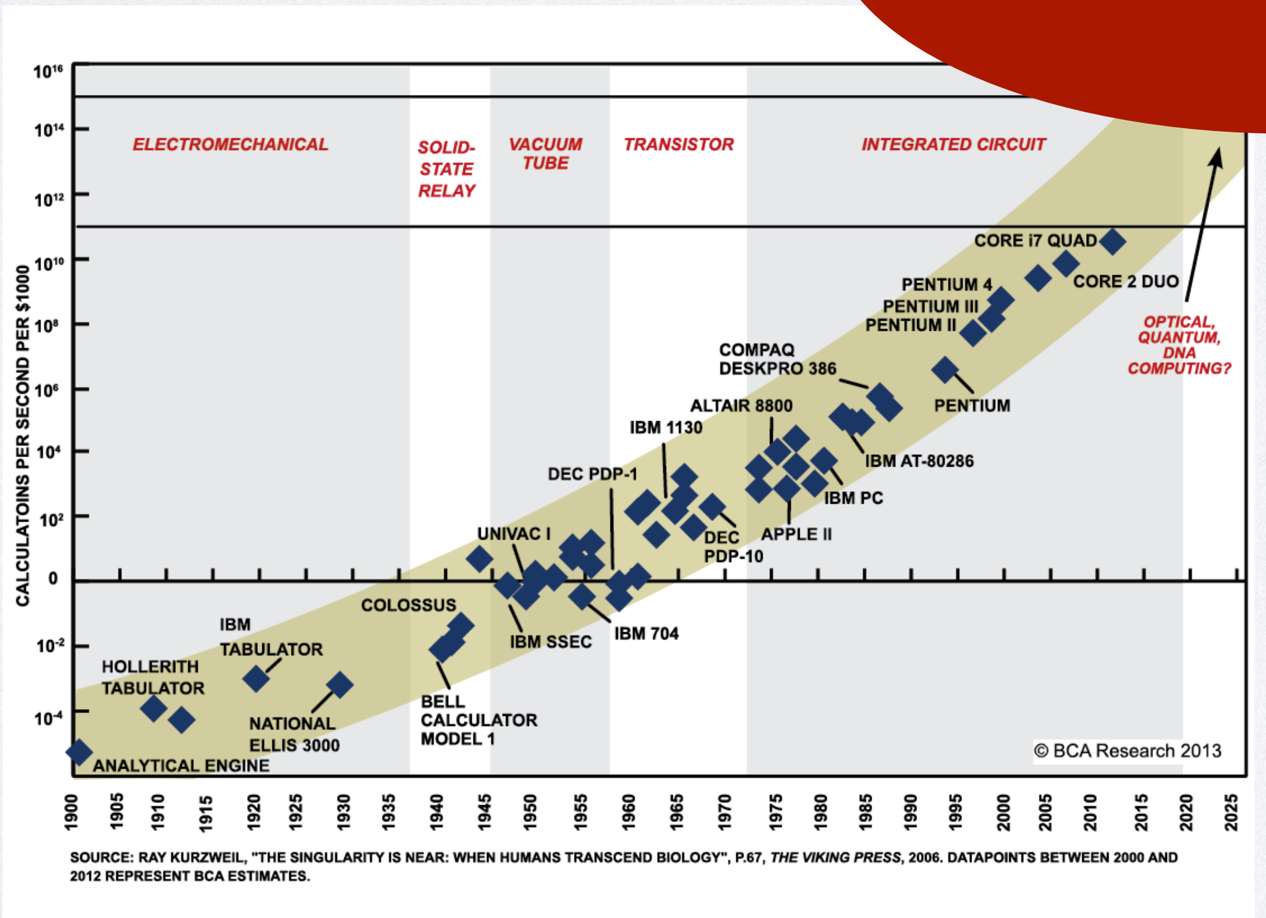


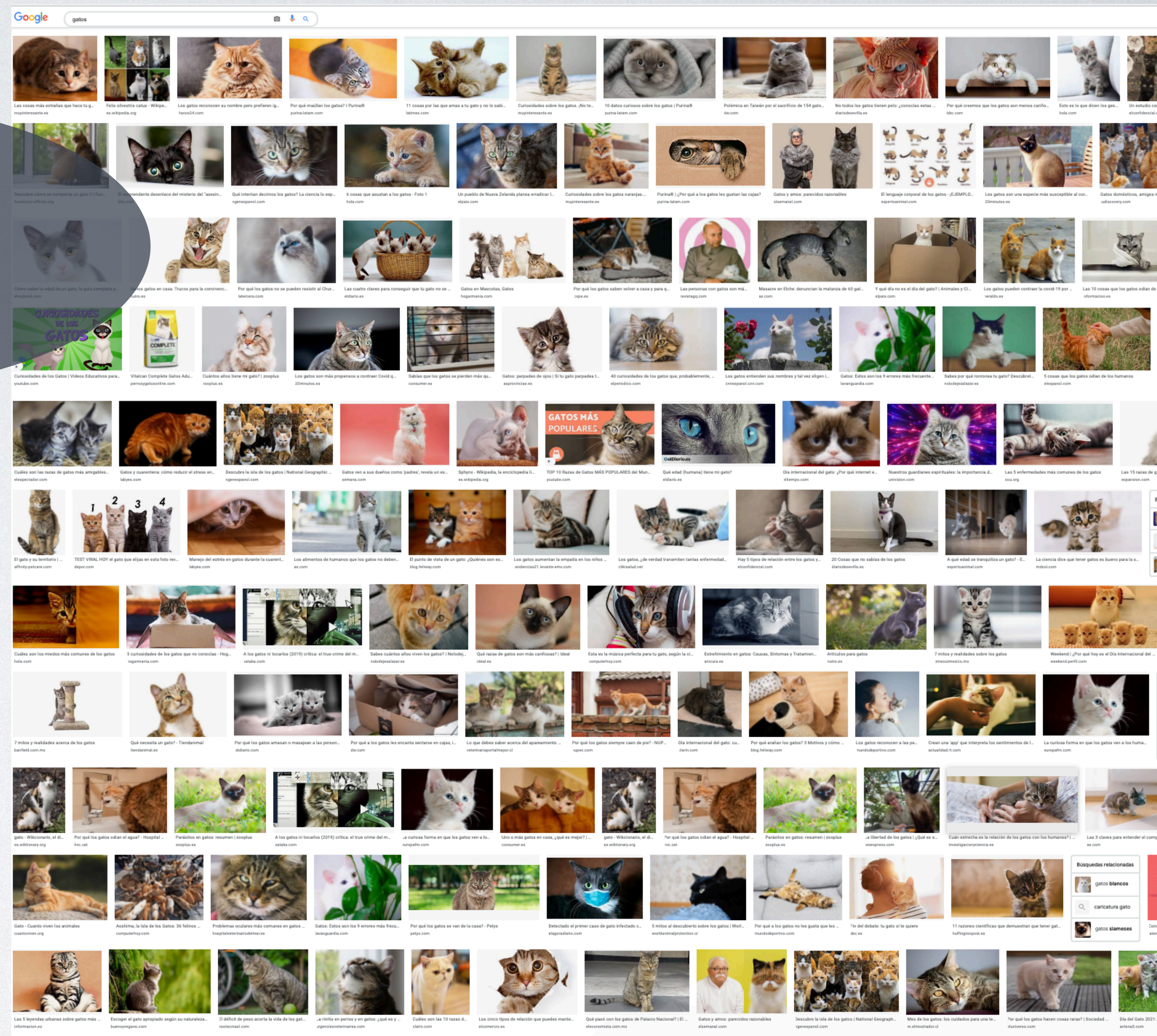
Algorithms

Data

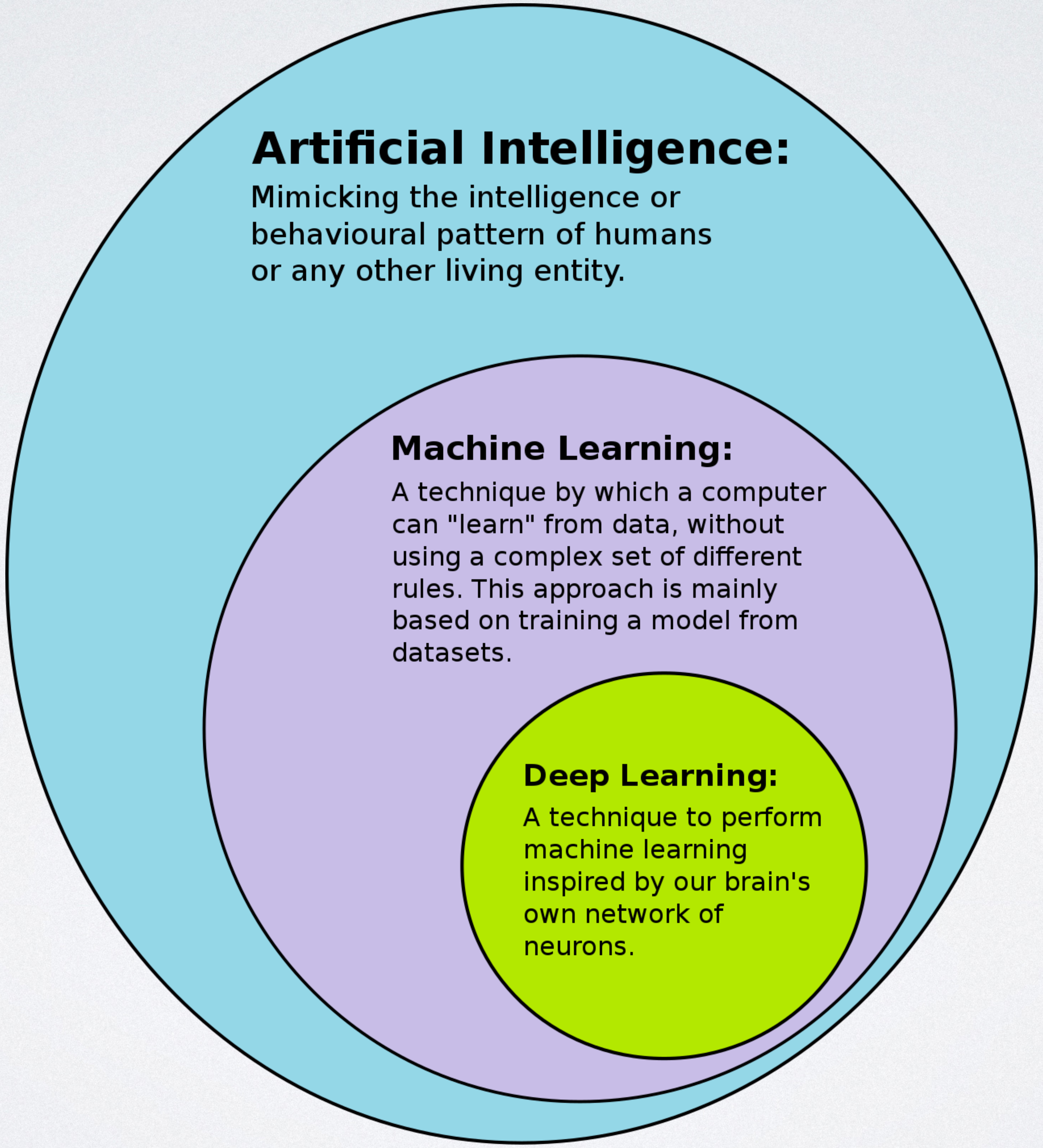
A.I. revolution

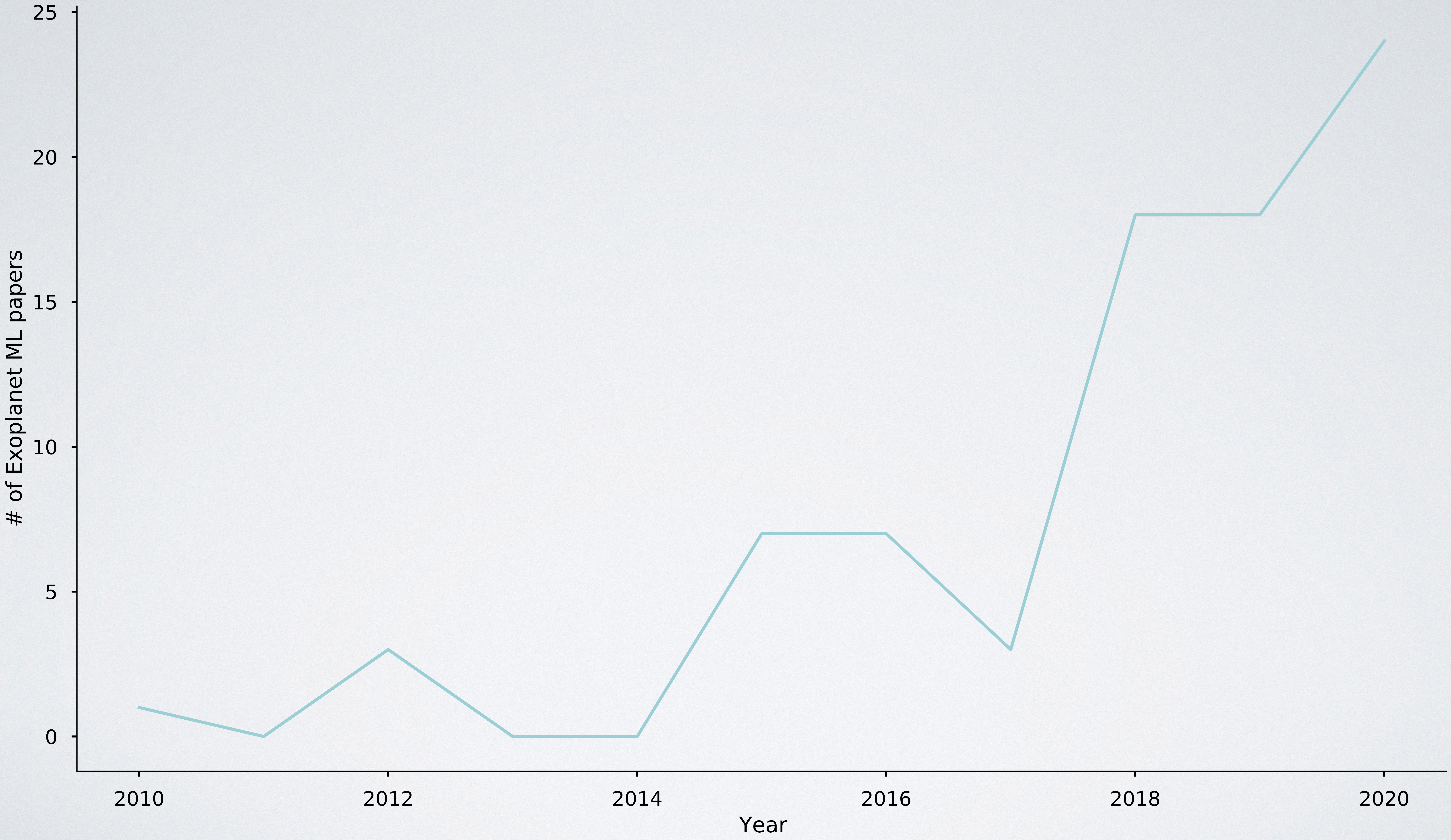
Computing power



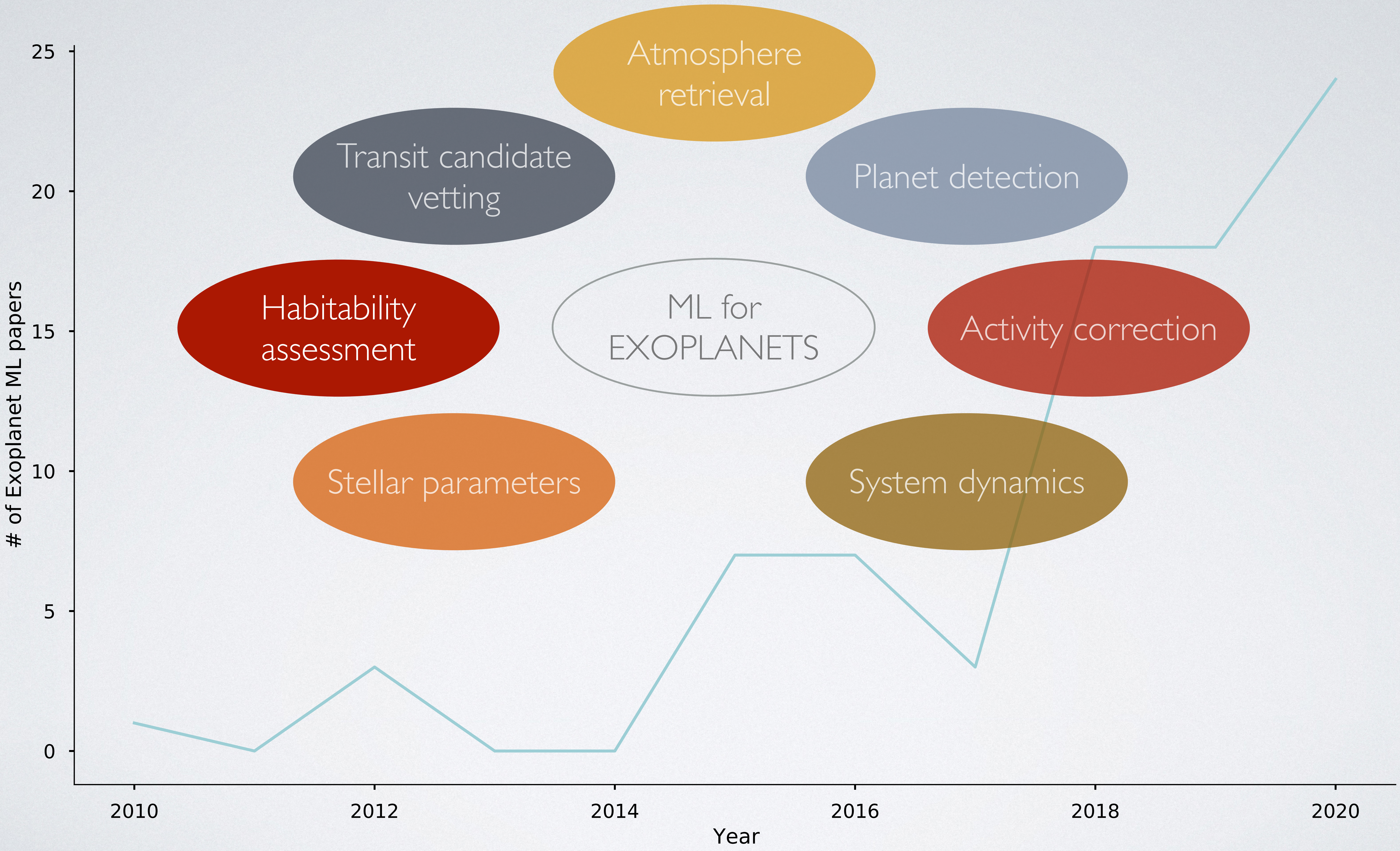


ARTIFICIAL INTELLIGENCE





25
20
15
10
5
0
# of Exoplanet ML papers
2010
2012
2014
2016
2018
2020
Year

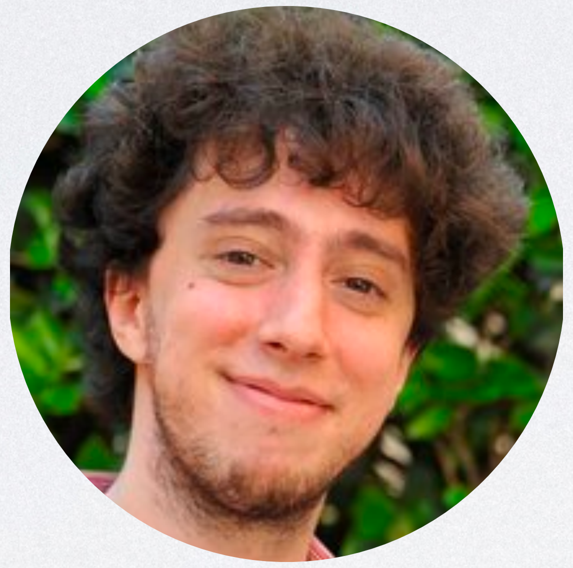

Atmosphere retrieval
Transit candidate vetting
Planet detection
Habitability assessment
ML for EXOPLANETS
Activity correction
Stellar parameters
System dynamics
# of Exoplanet ML papers
Year
0
5
10
15
20
25
2010
2012
2014
2016
2018
2020

ICIFI

Luis Agustín Nieto
(Computer science)

Exoplanet detection in RV data.

Deep Learning



Alejandro Hacker
(Physics)

TESS follow-up

Population parameter inference

Hierarchical Bayesian Models

Juan Serrano
(Astronomy)

ML for instrument optimisation

TESS follow-up observations

Blind source separation

Andrea Buccino
(Physics)

Stellar Activity in low-mass stars

Dynamo theory

Carla Oviedo
(Astronomy)

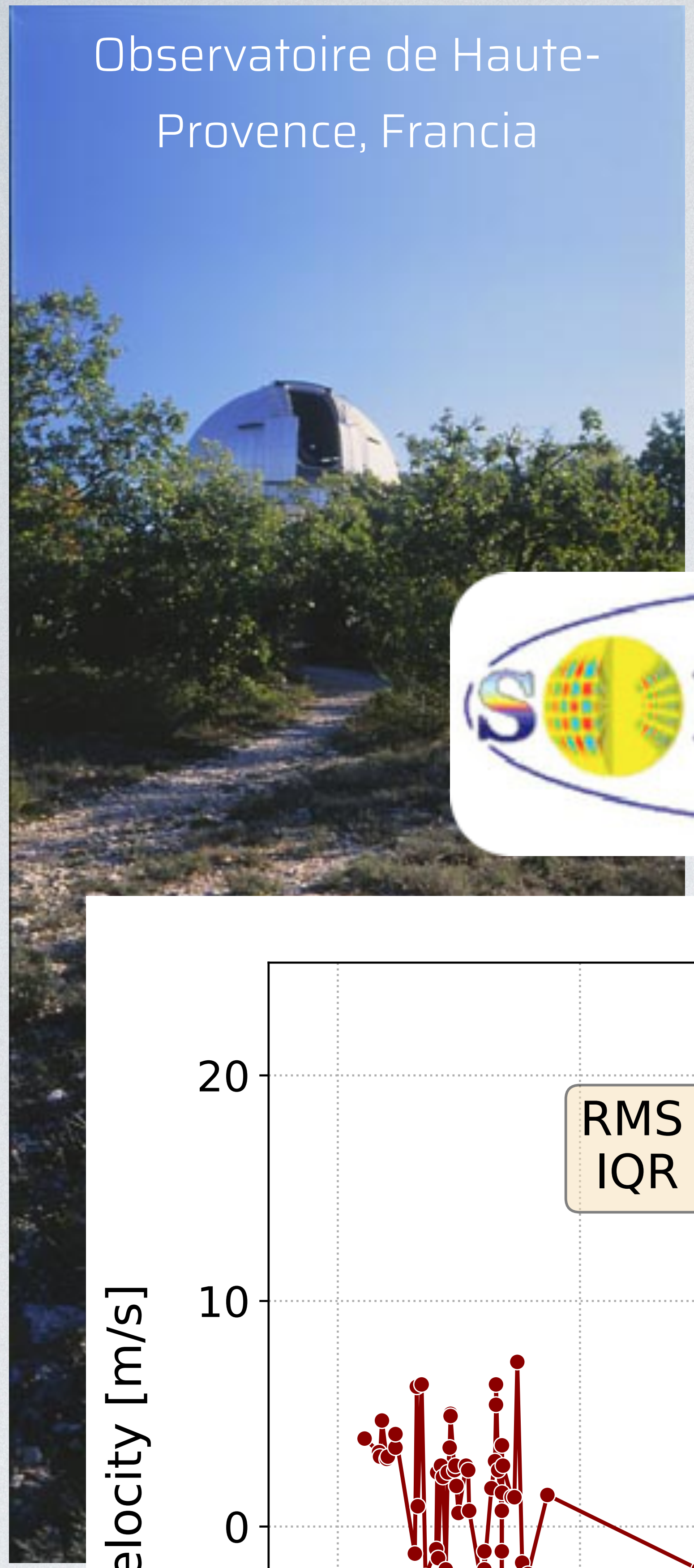
Effect of activity on RVs

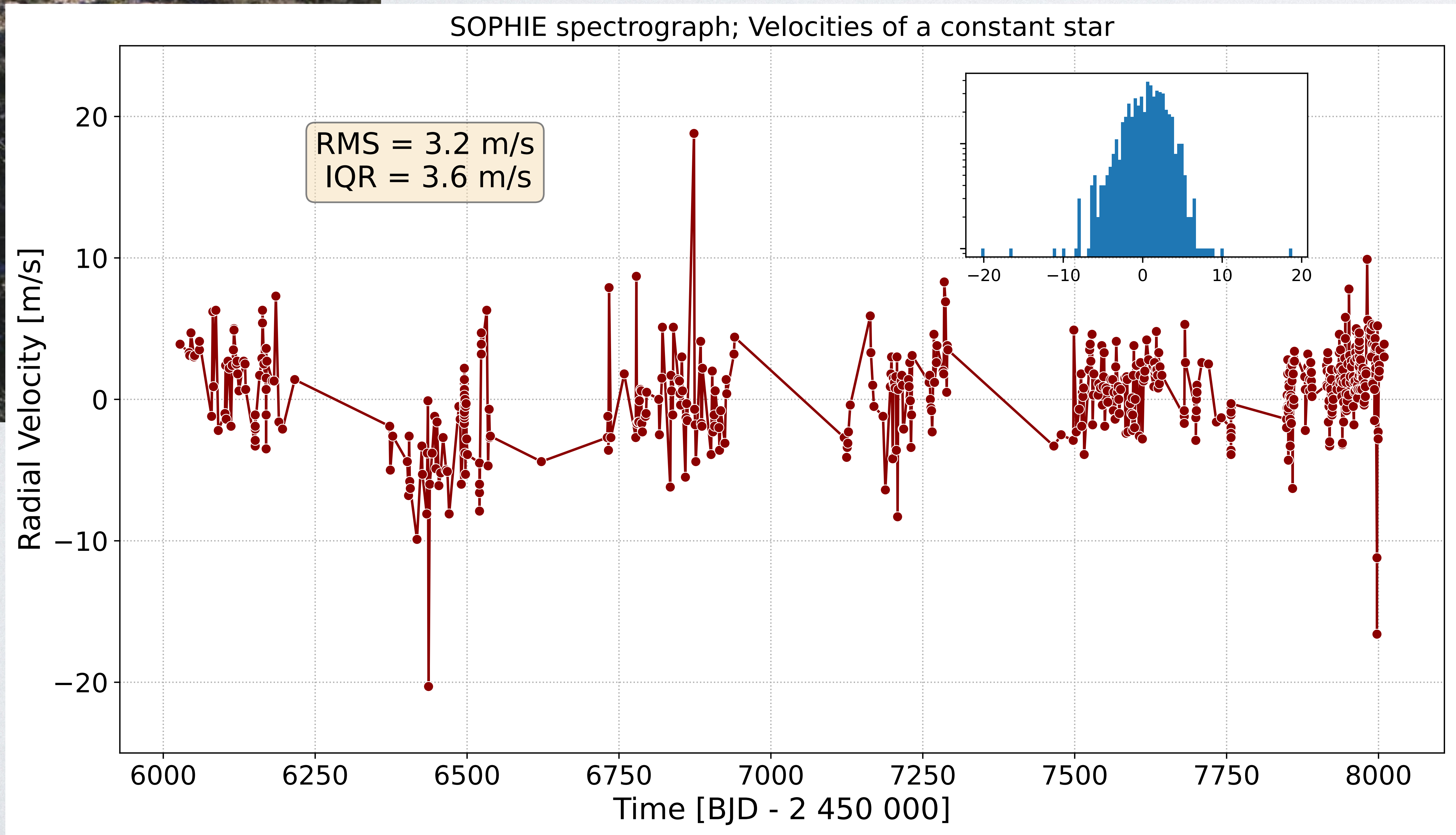
Leila Asplanato
(Physics)

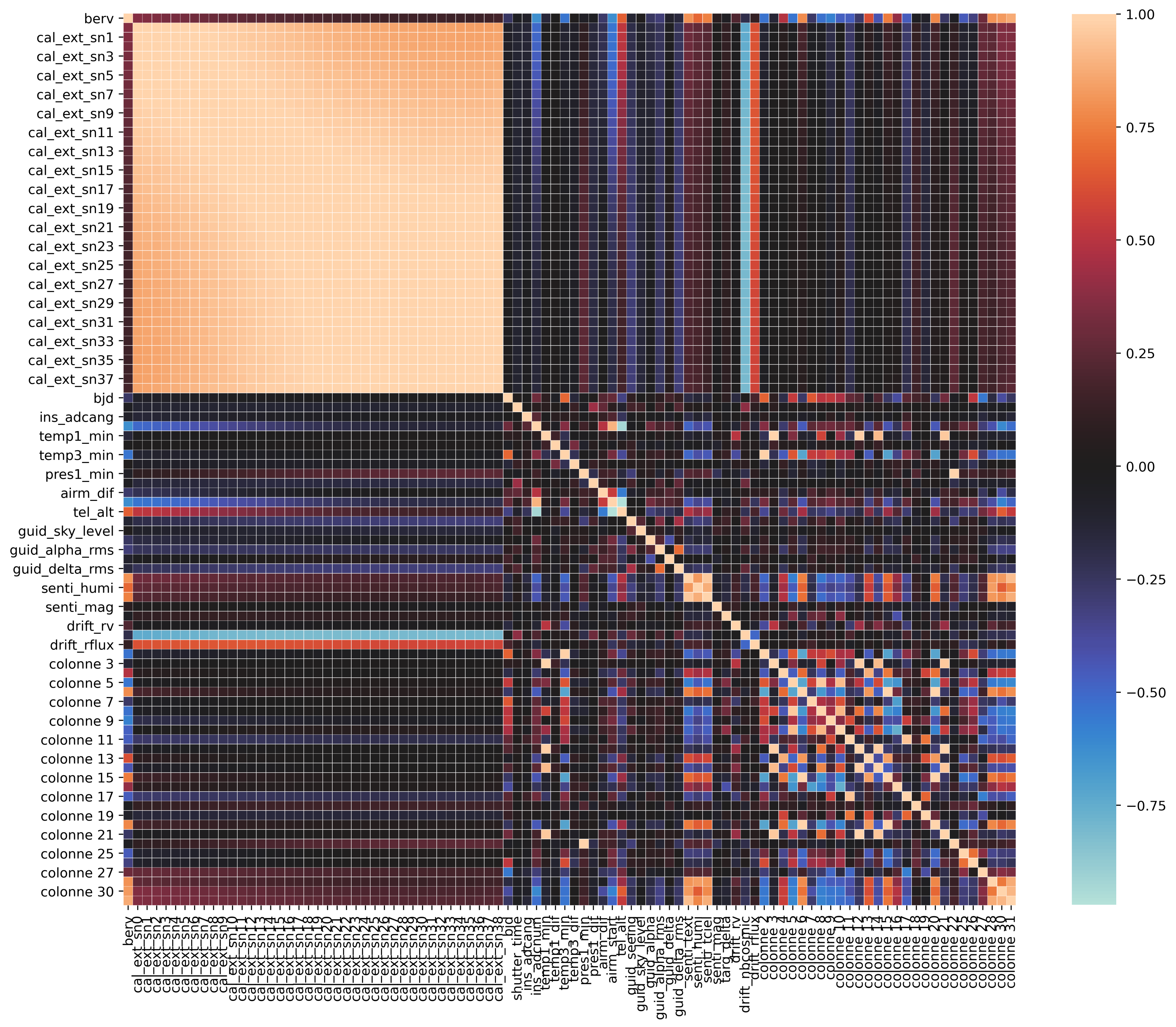
Dropout studies in University

Causal inference

ML FOR INSTRUMENT OPTIMISATION







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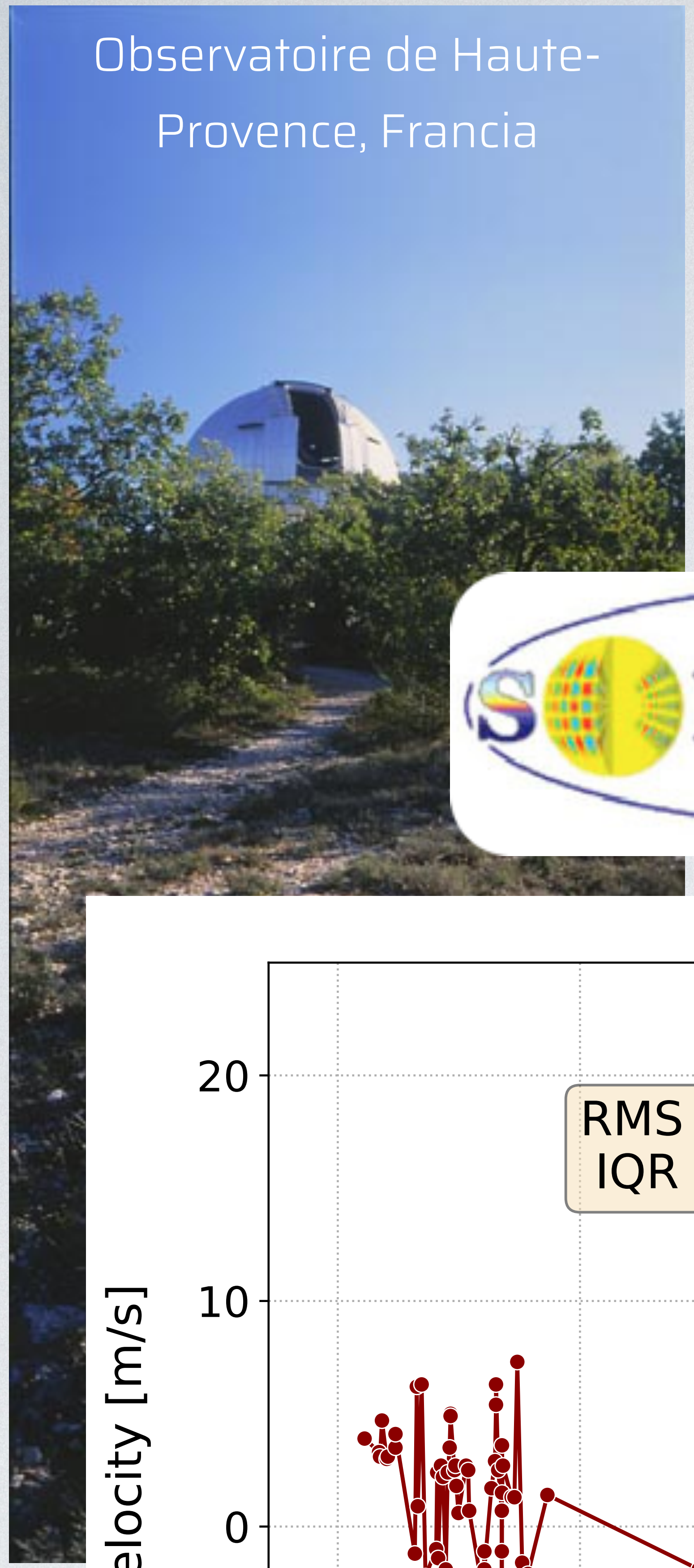
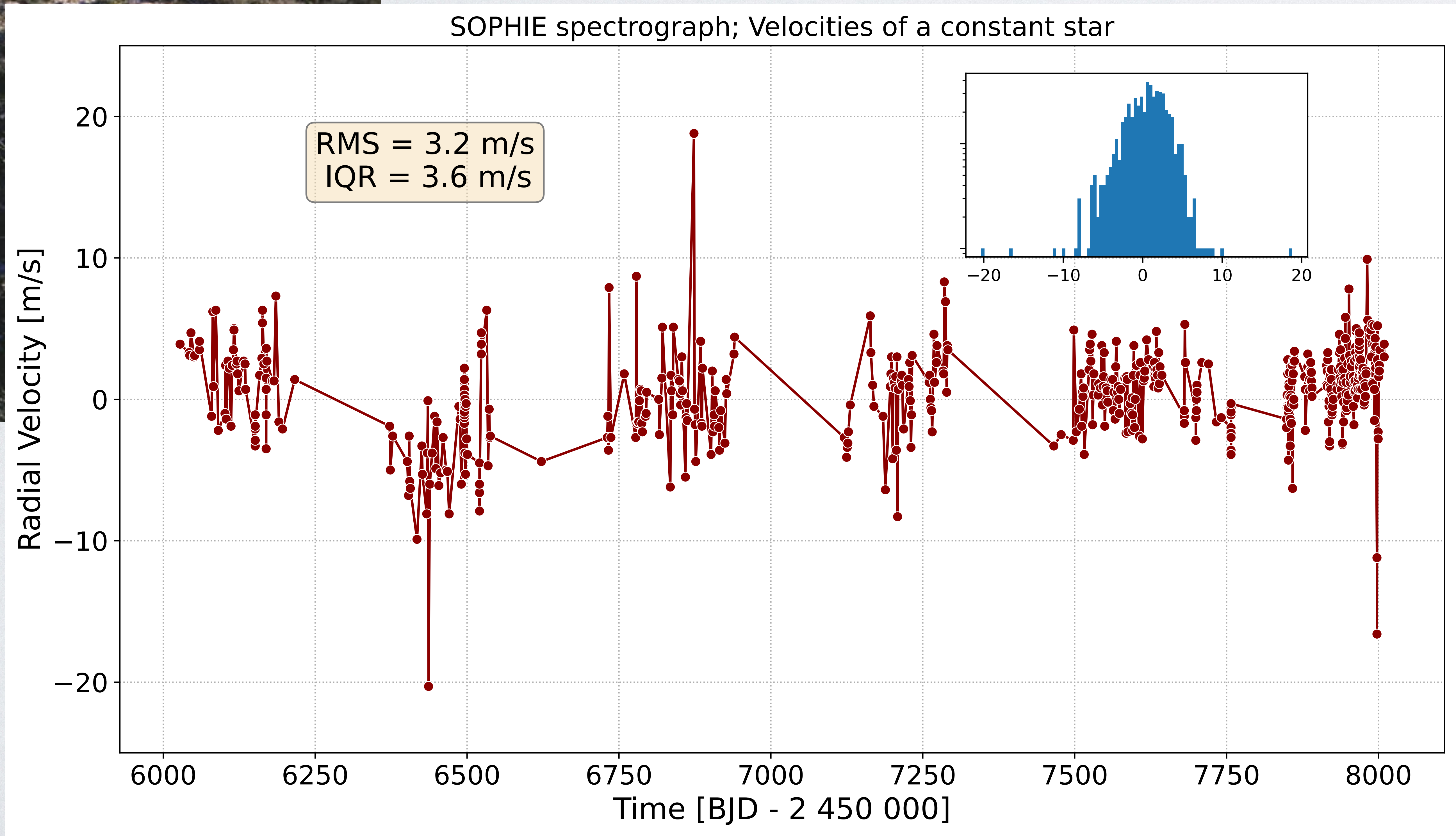
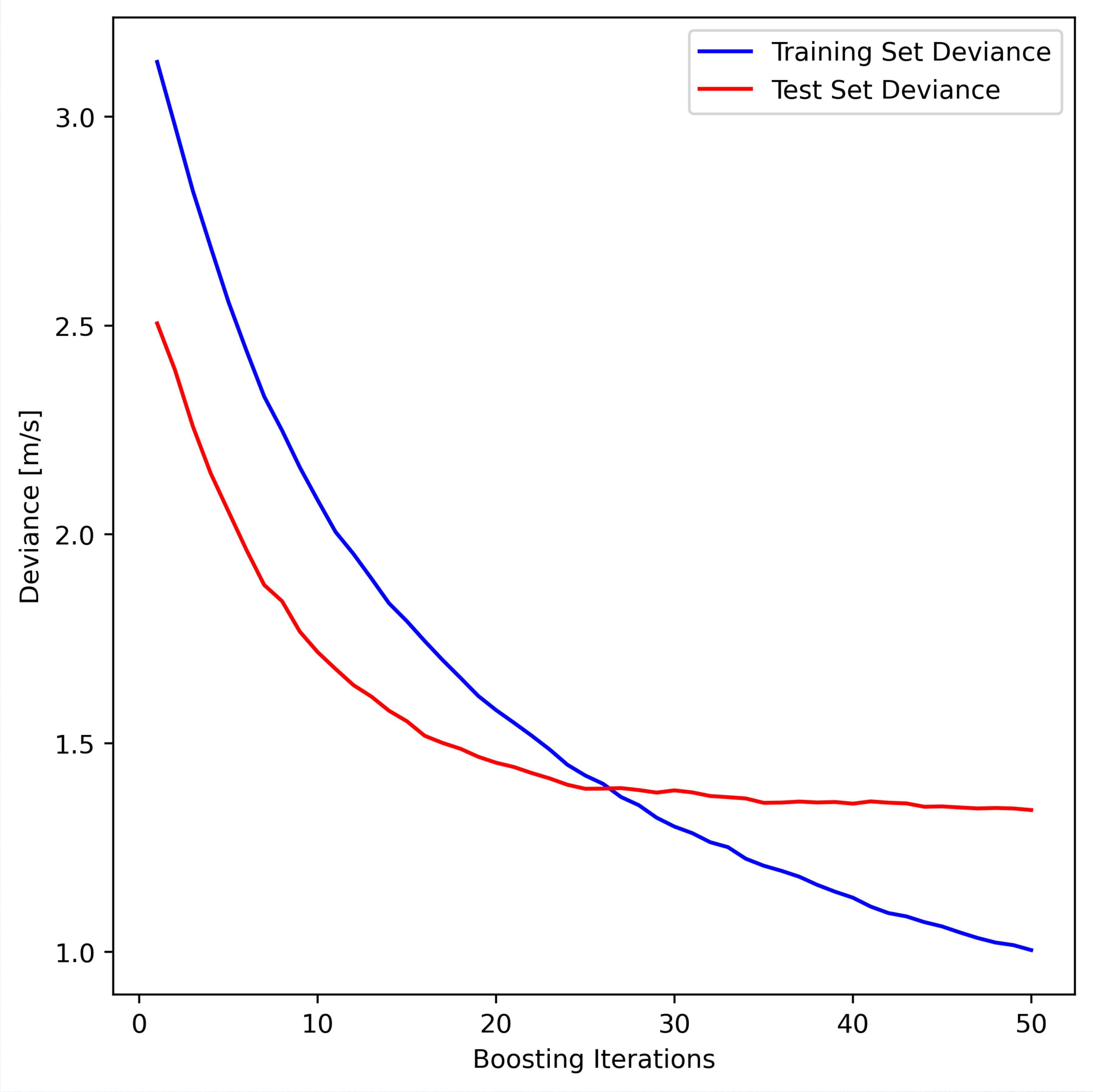
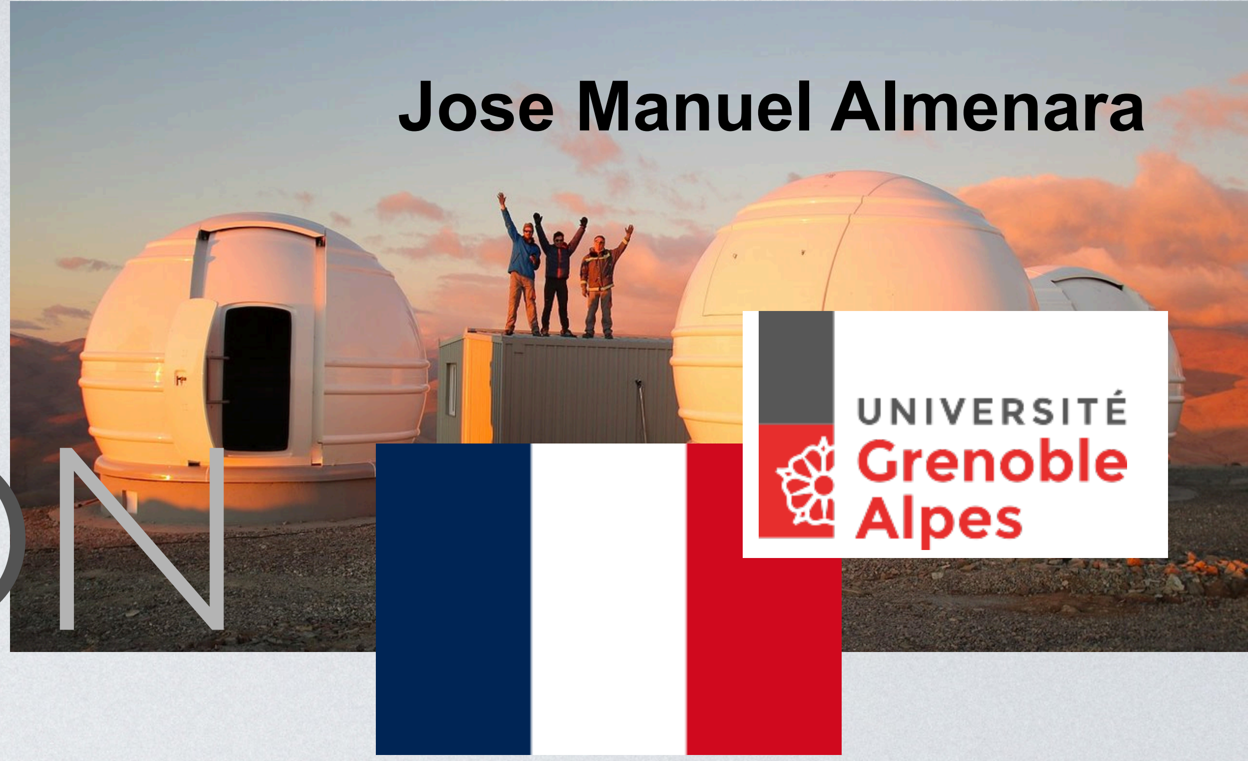
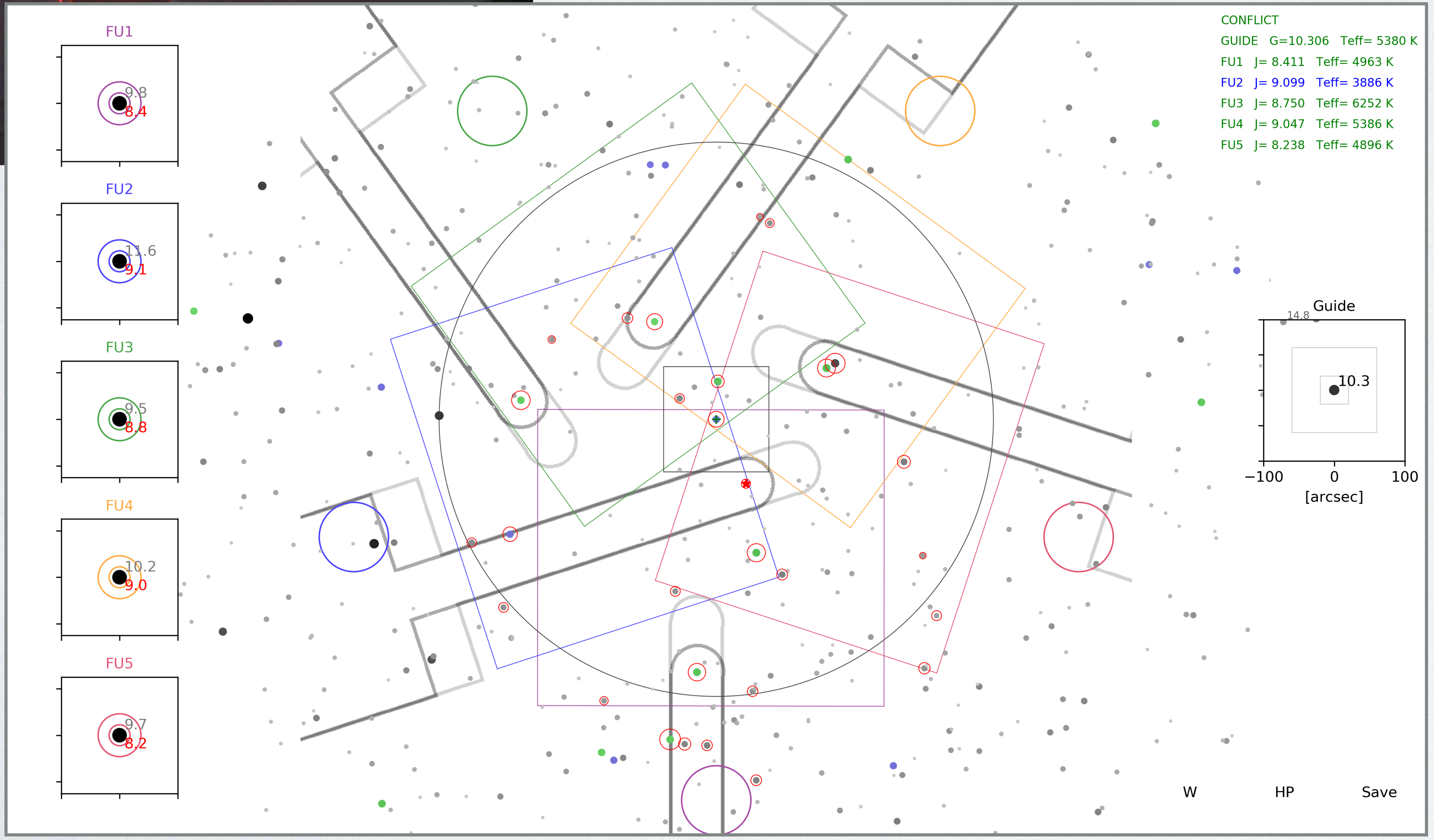


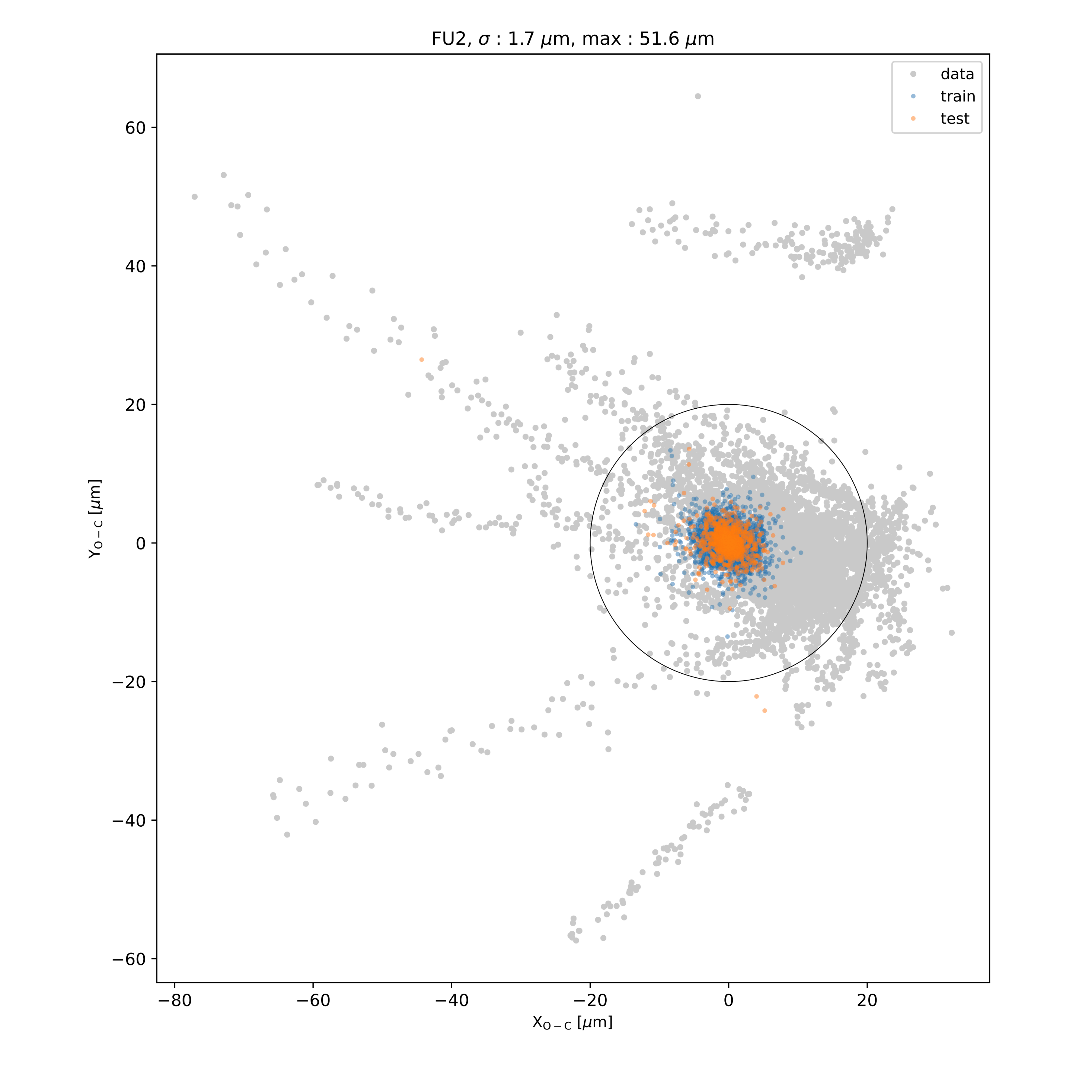




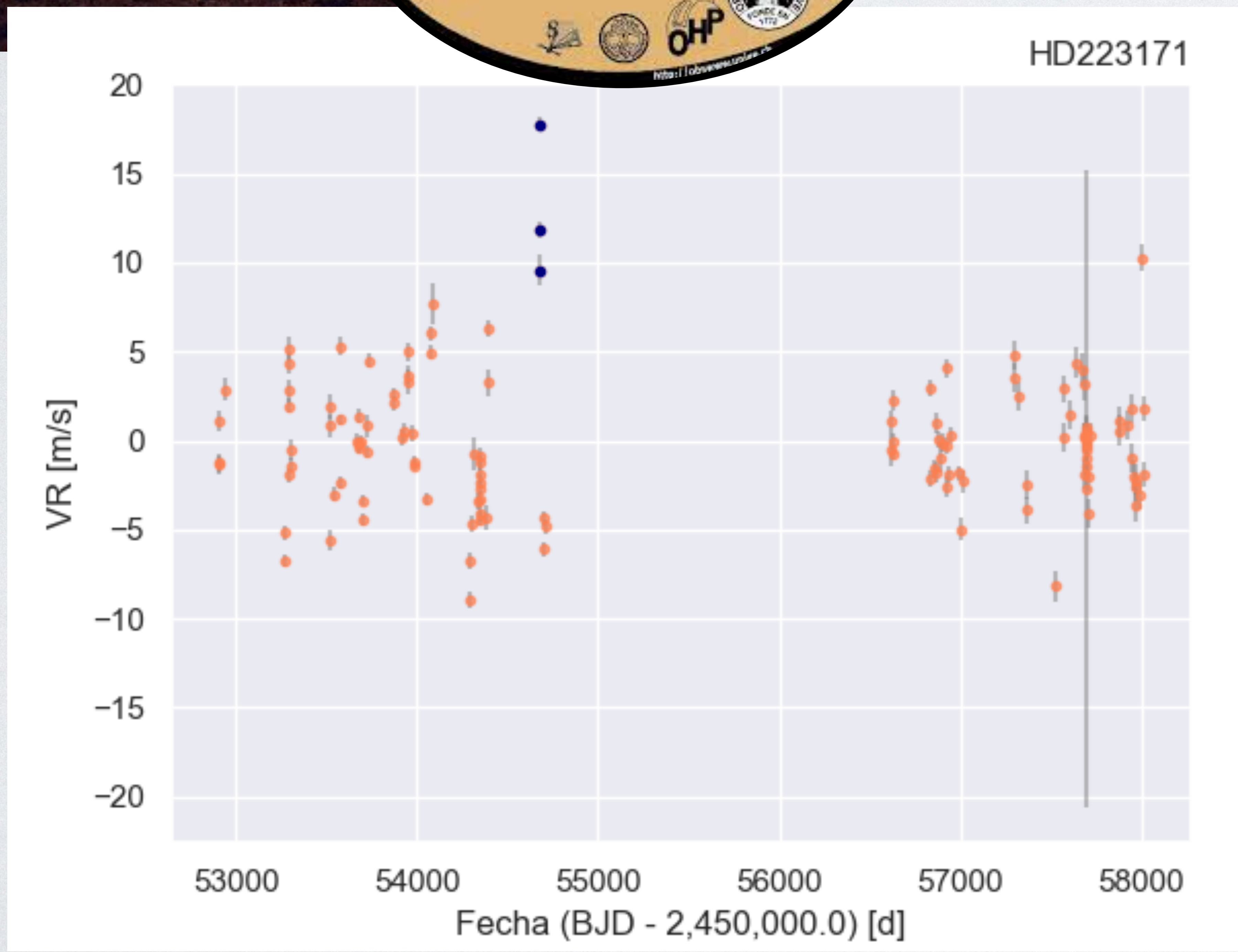
ML TO IMPROVE INSTRUMENT OPERATION

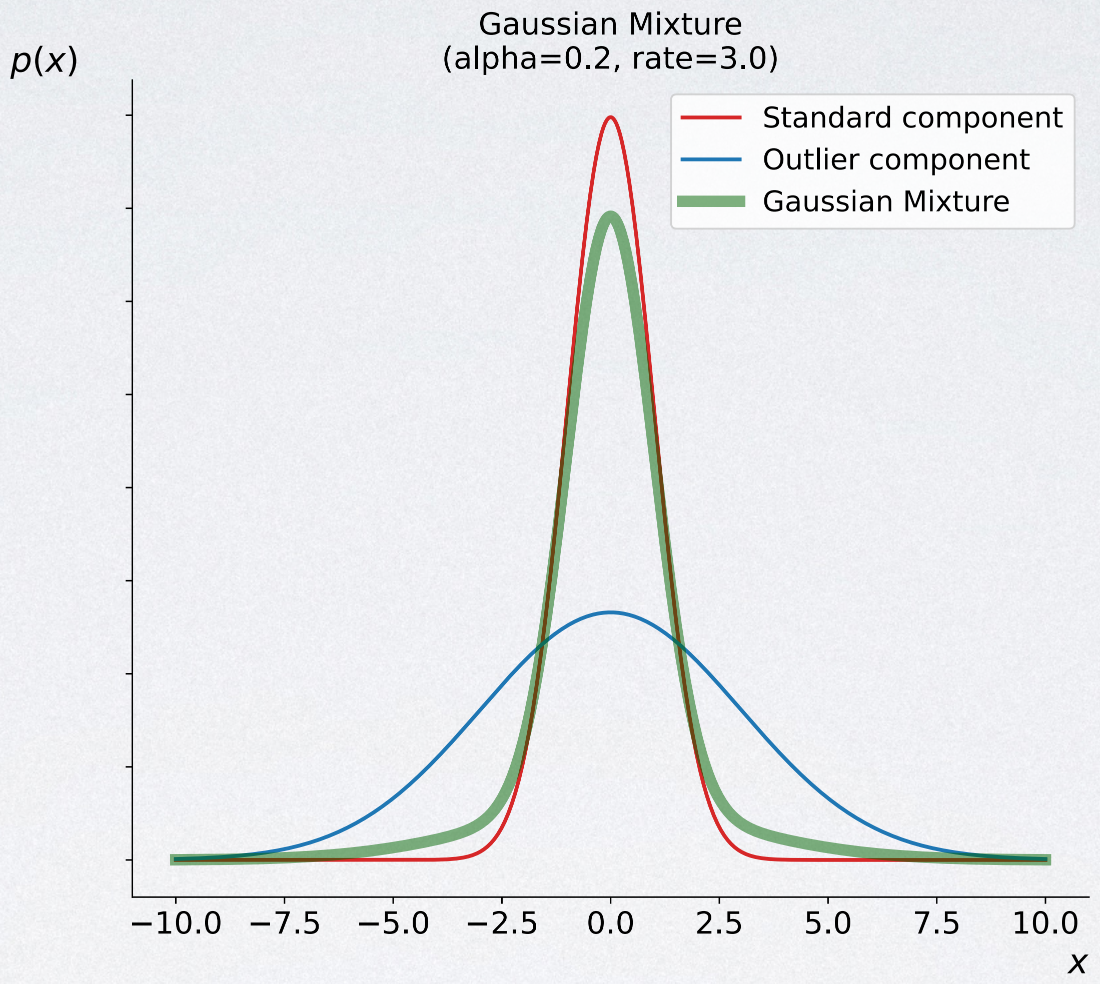




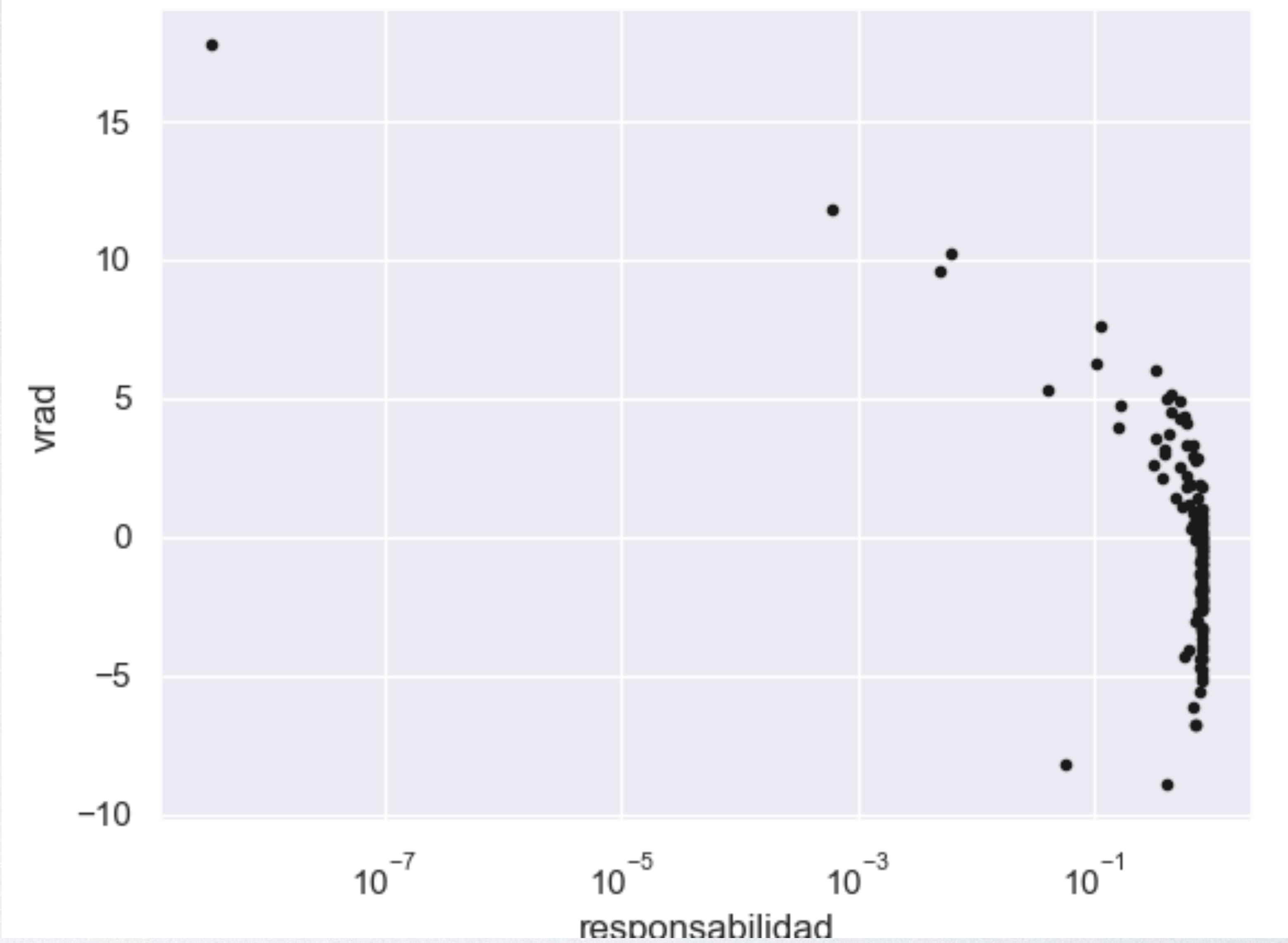


MIXTURE MODELS TO ACCOUNT FOR OUTLIERS





$$p(x) = (1-\alpha)N(0,\sigma) + \alpha N(0, r\sigma)$$



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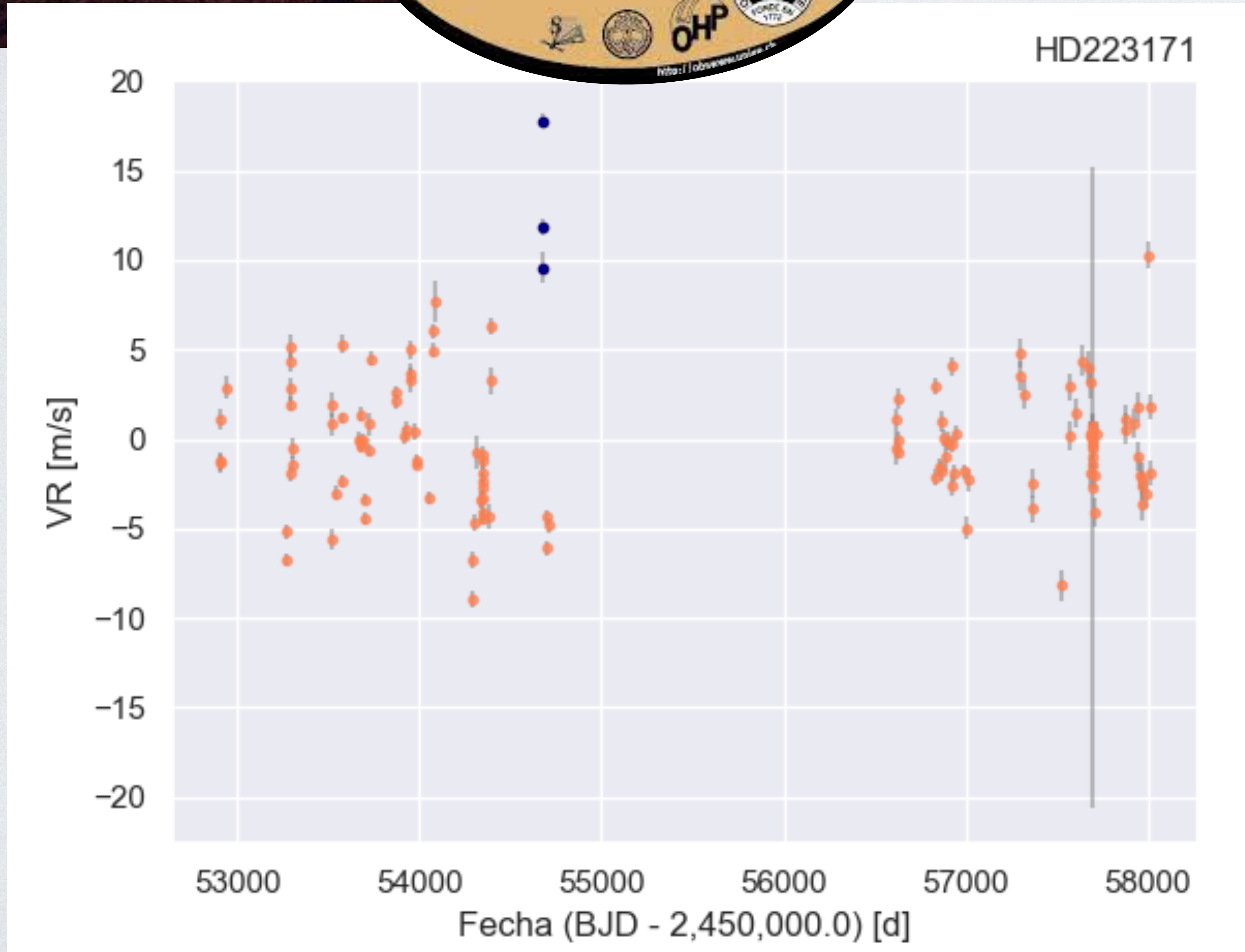

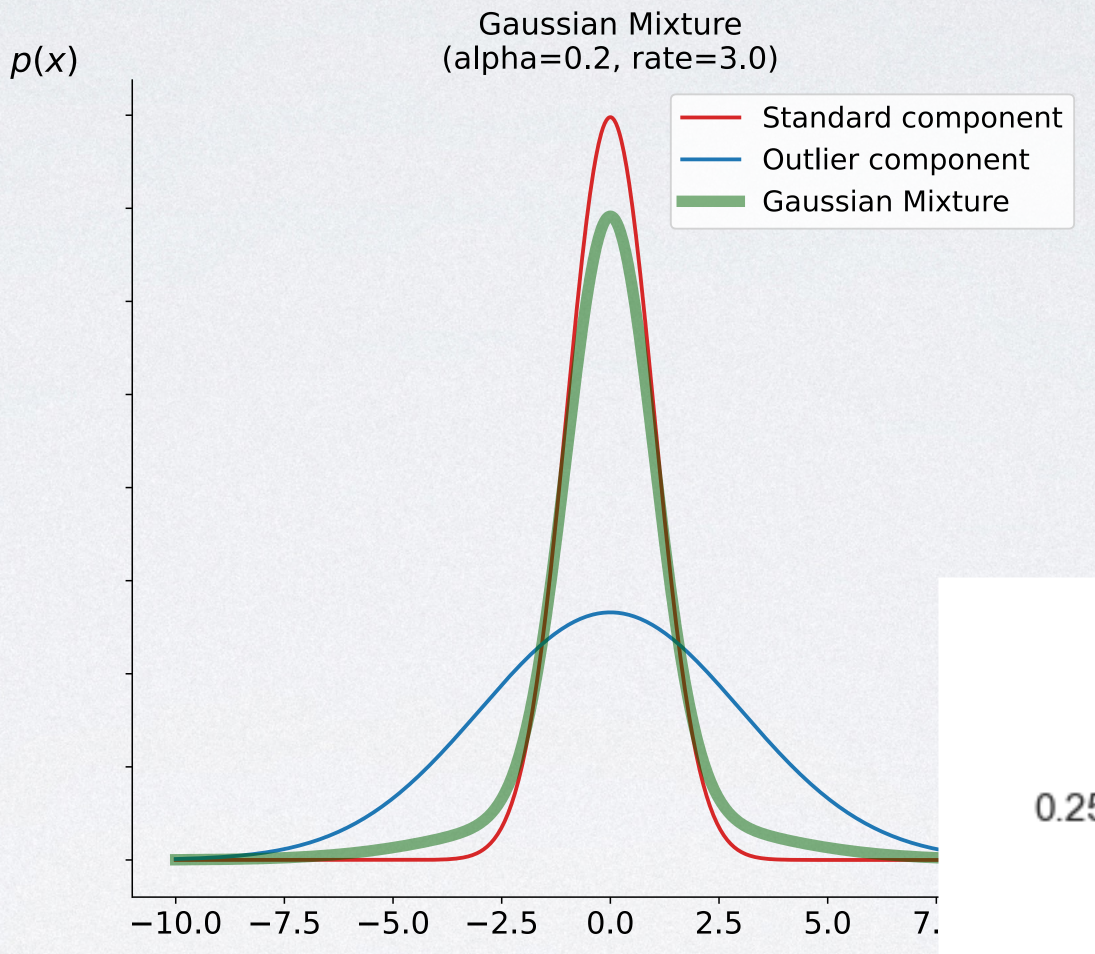

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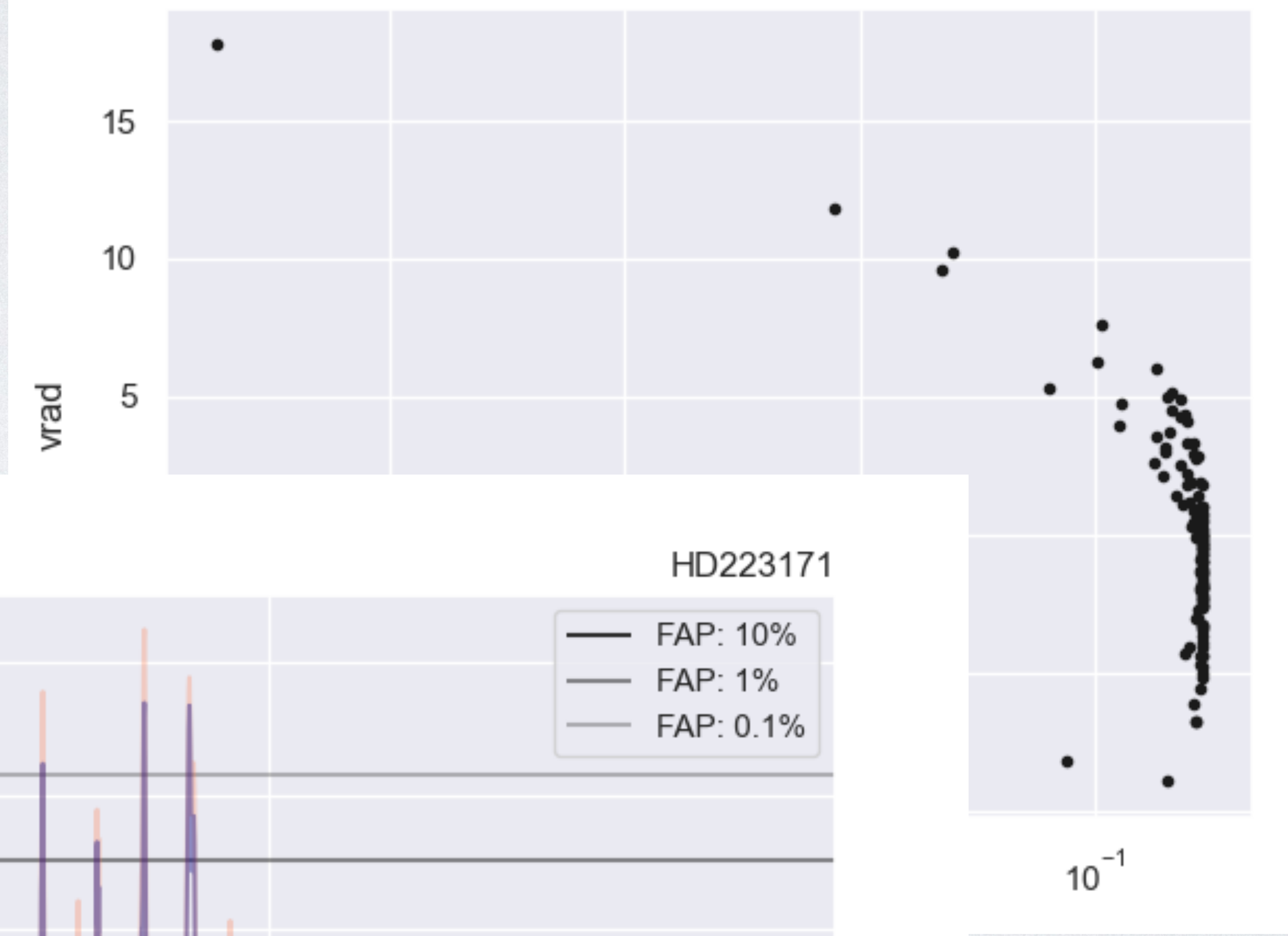
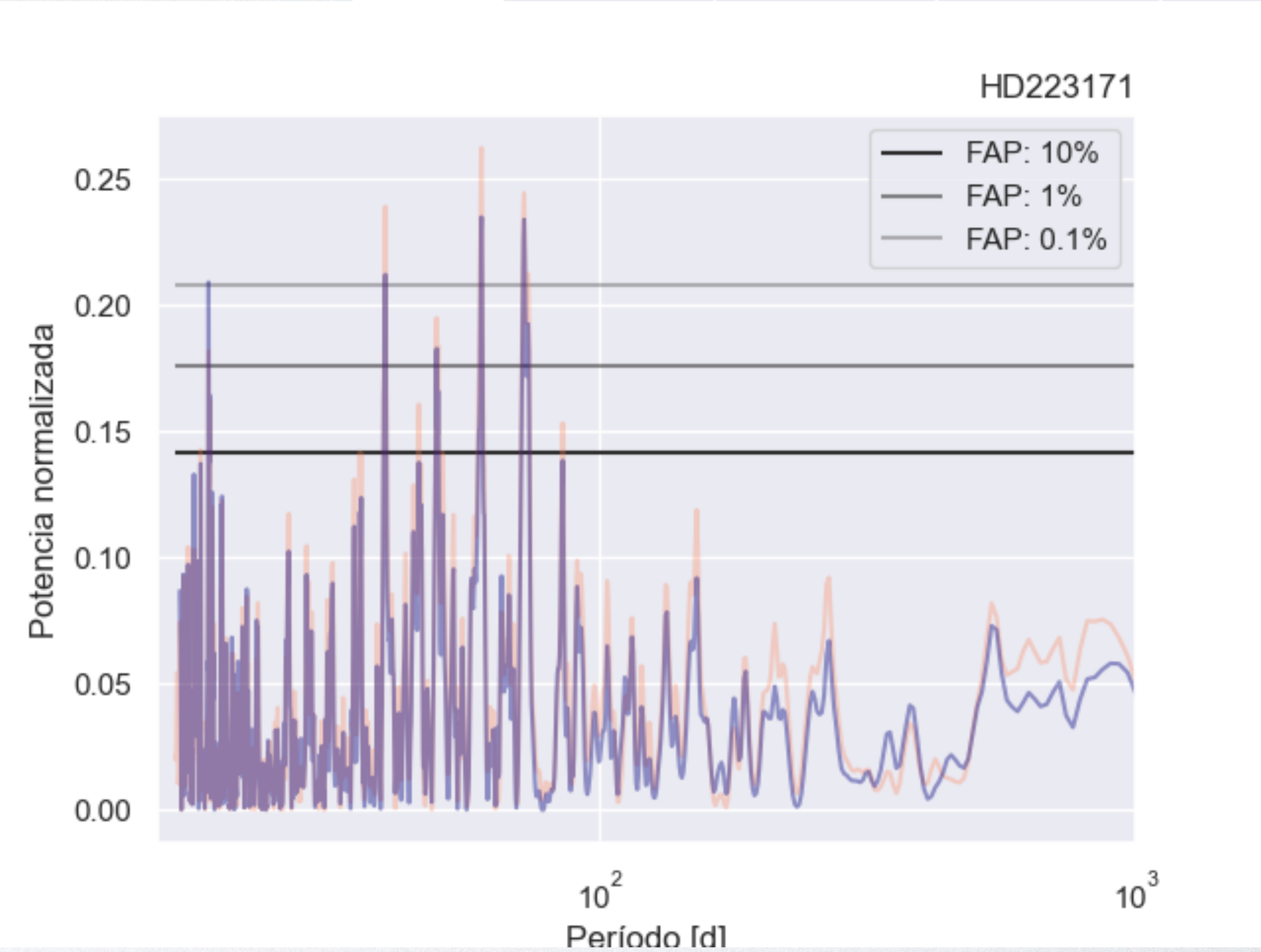




Astronomy & Astrophysics manuscript no. ExoplaNNET-arvix-2
July 4, 2023

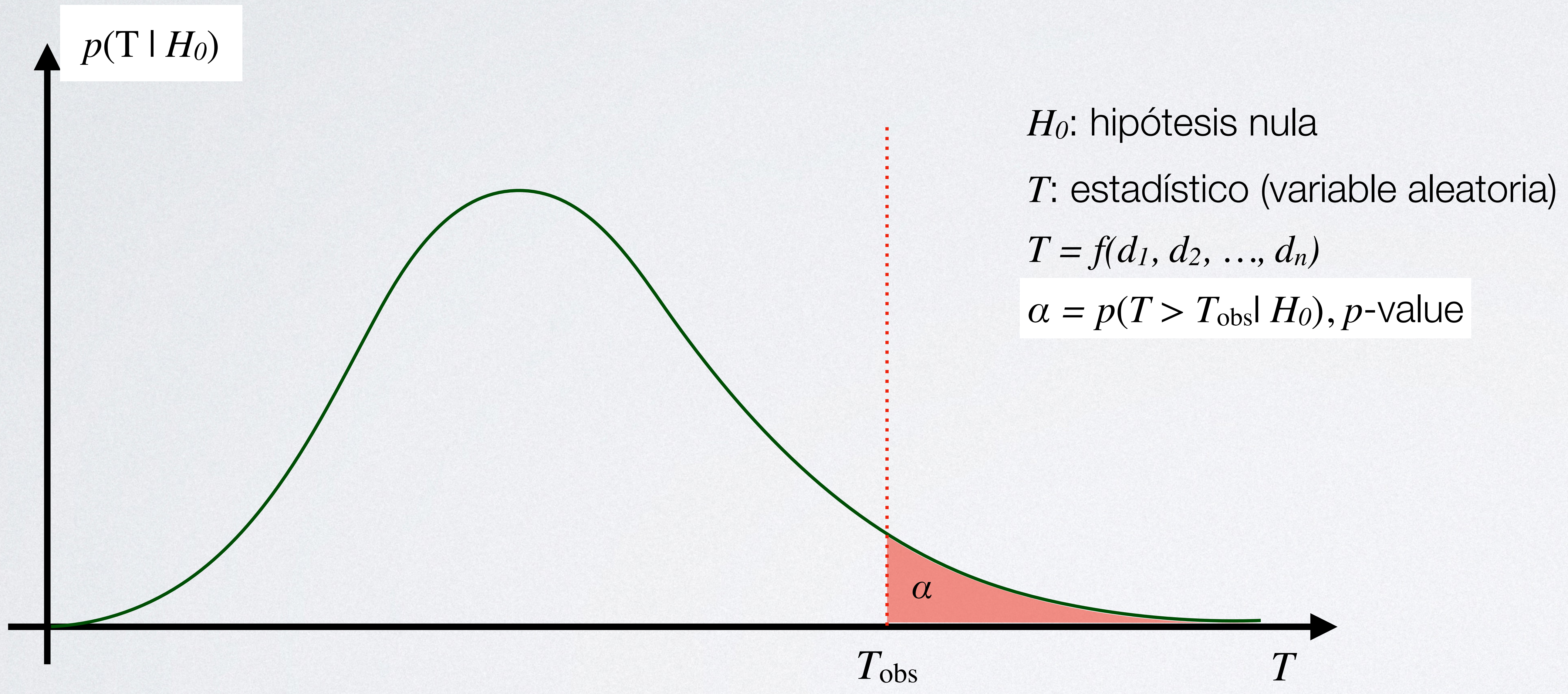
Luis Agustín Nieto

ExoplANNET: A deep learning algorithm to detect and identify planetary signals in radial velocity data

L. A. Nieto[1,2] & R. F. Díaz[2]

OUR BASELINE MODEL

The classical approach to detecting signals in RV time series



Analytical distributions depend strongly on hypotheses that are **rarely satisfied**.

Simulations (*bootstraping*) under the null are performed to alleviate this. This is **computationally expensive**.

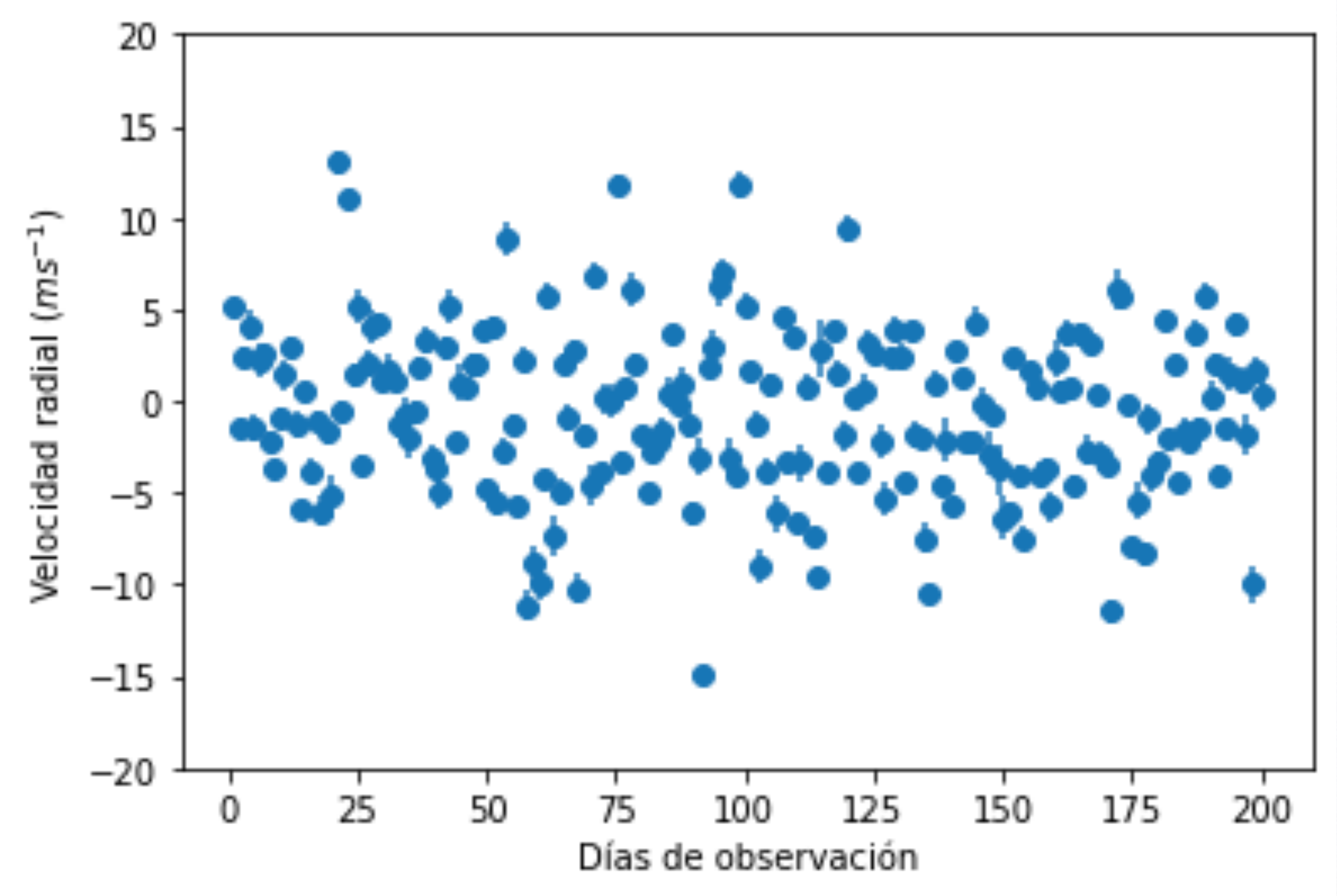
Theoretical issues with *p*-values in general —> Bayesian statistics.

DATA

RV surveys do not provide LARGE amounts of data. —> We resort to simulations to produce an appropriate training set.

Realistic noise

- White (photon) noise.
- Pulsations, oscillations.
- Rotational modulation.



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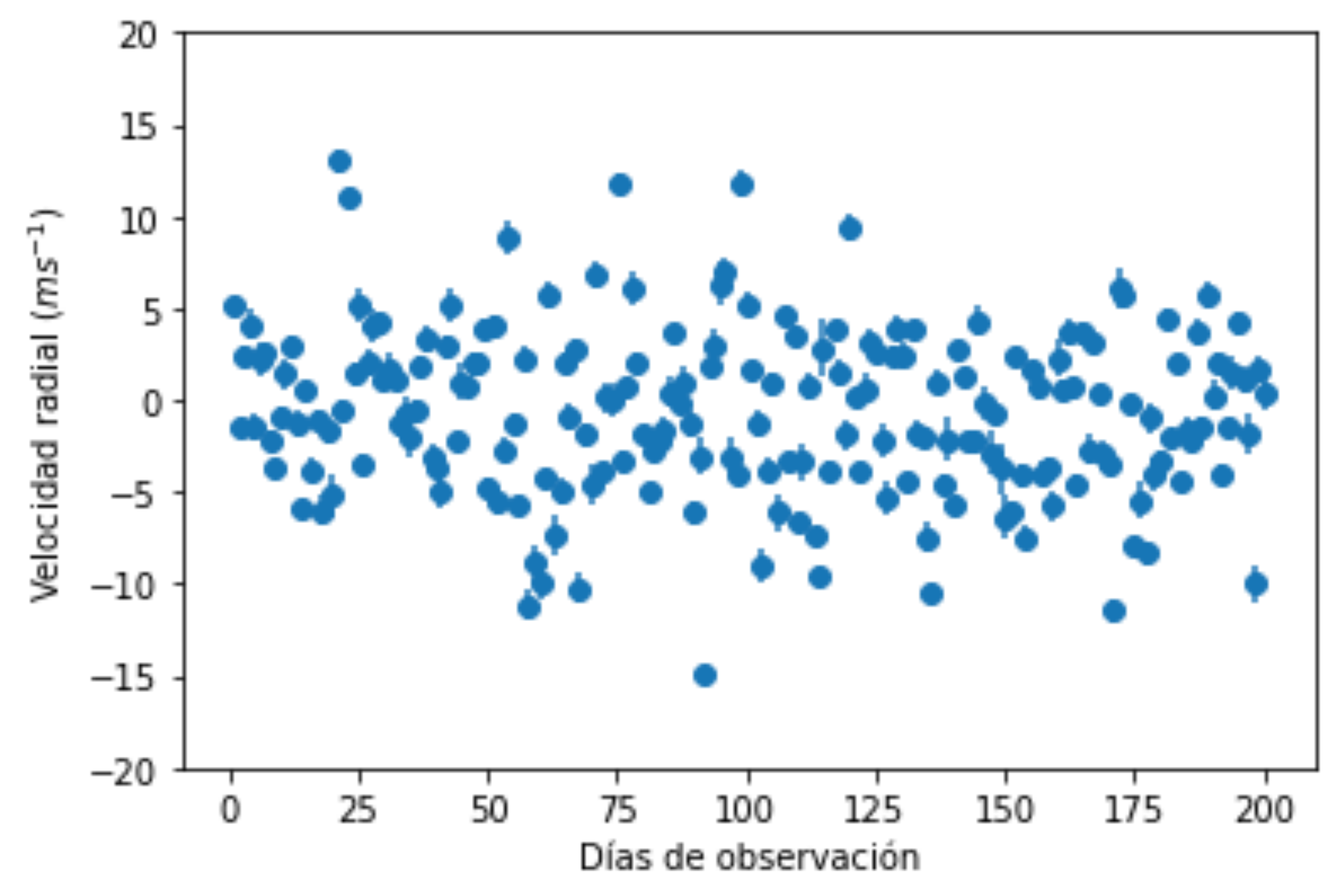
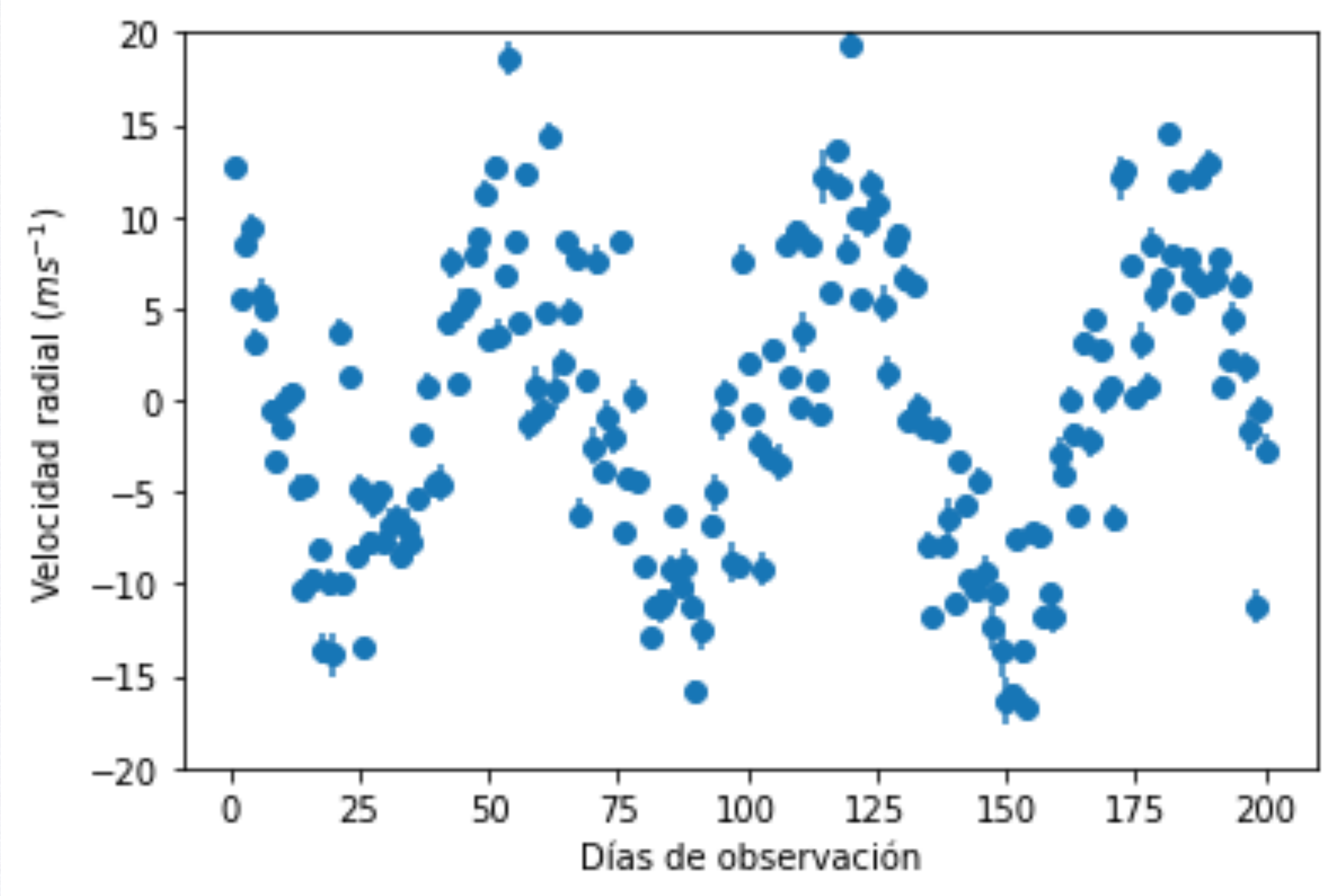


Circular planets

- Period ~ U[10 d, 100 d]
- Amplitudes ~ log-flat[0.1 m/s, 10 m/s]
- Nplanets in {0, 1, 2, 3, 4}



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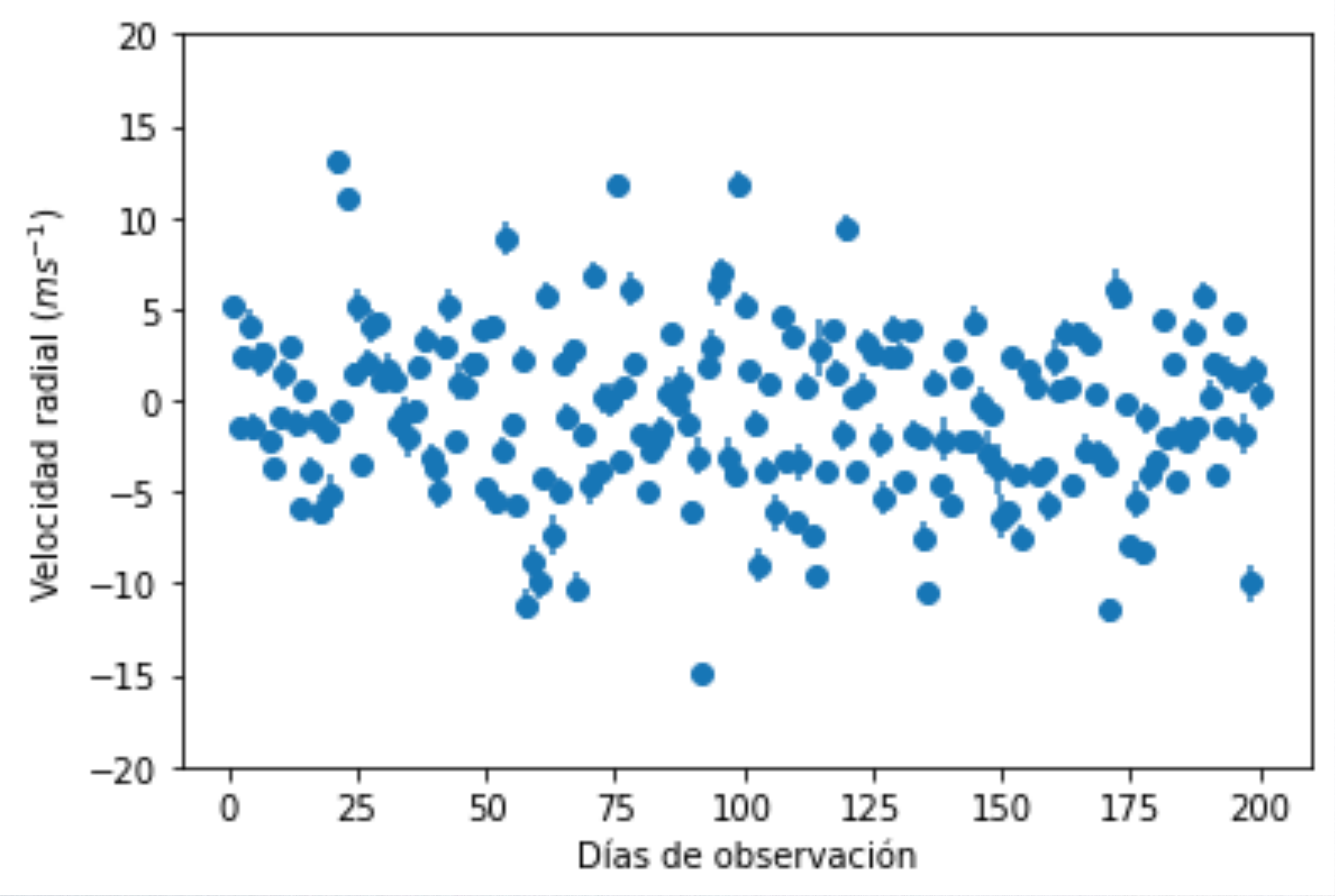

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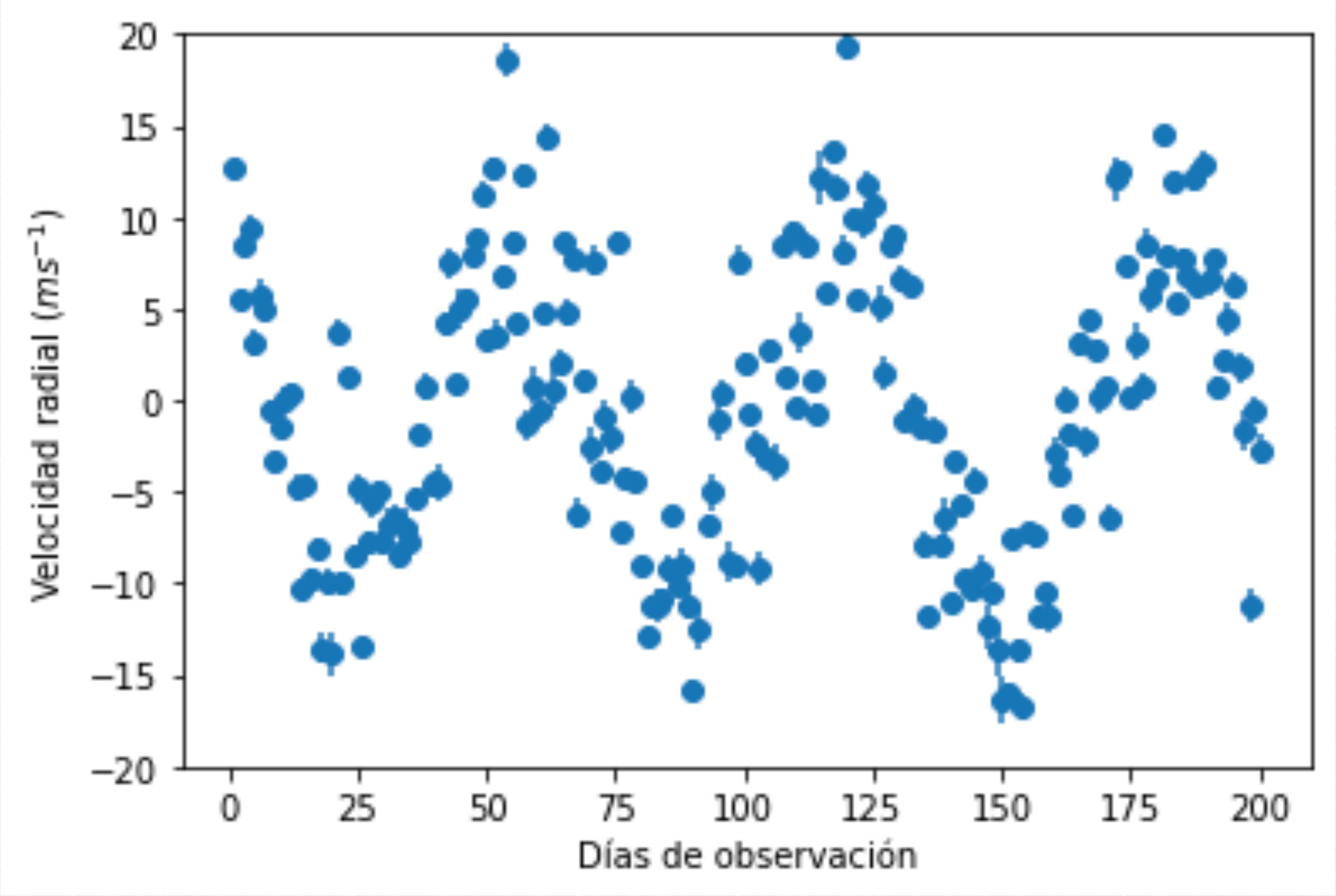

Parameters for noise simulations taken from real RV survey:

* HARPS high precision programme
(PI: Mayor —> Udry —> Díaz)

(ask me about noise simulations if you're interested!)

Time sampling

Pseudo-uniform (for historical reasons; not very realistic…)

DATA

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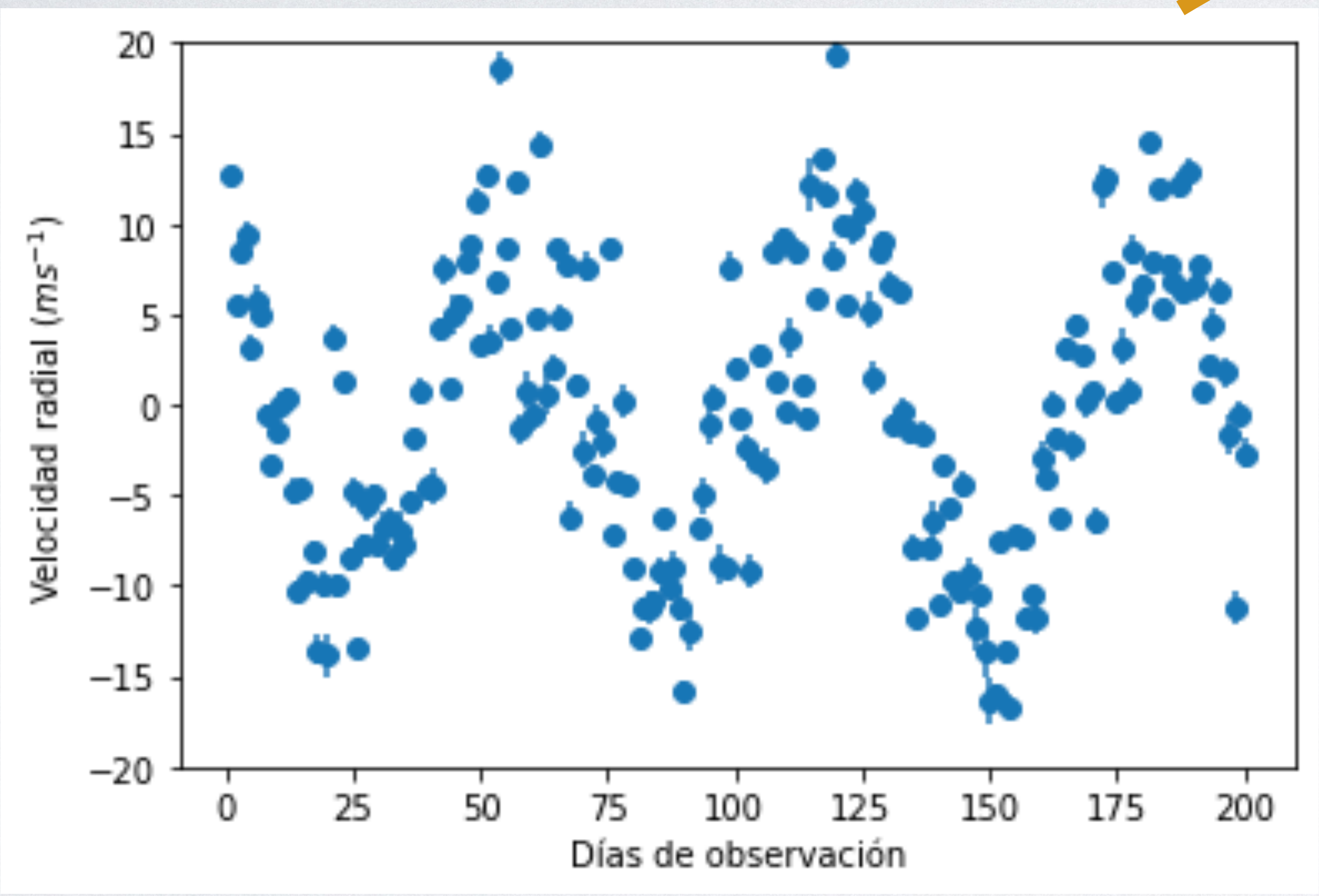

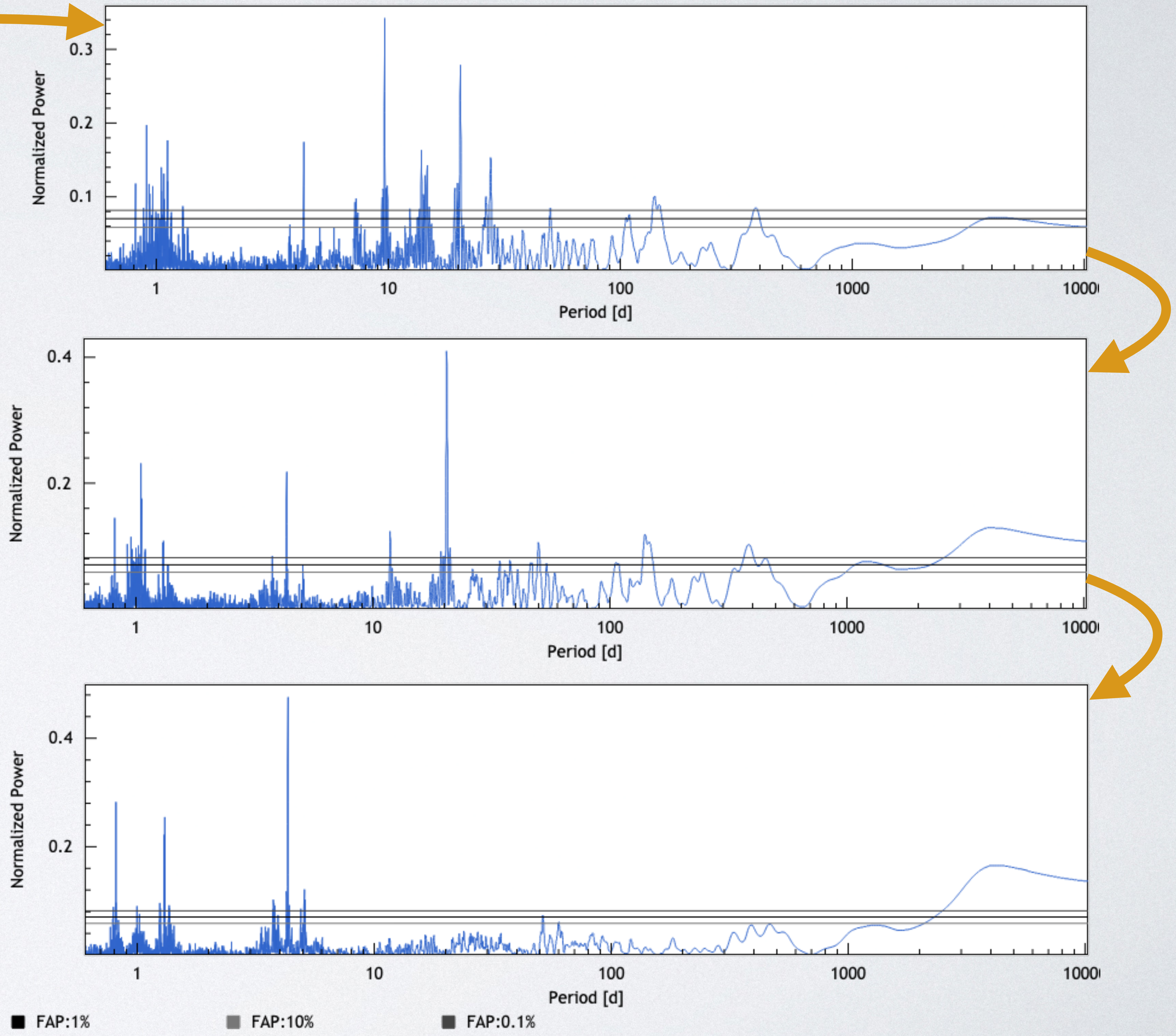

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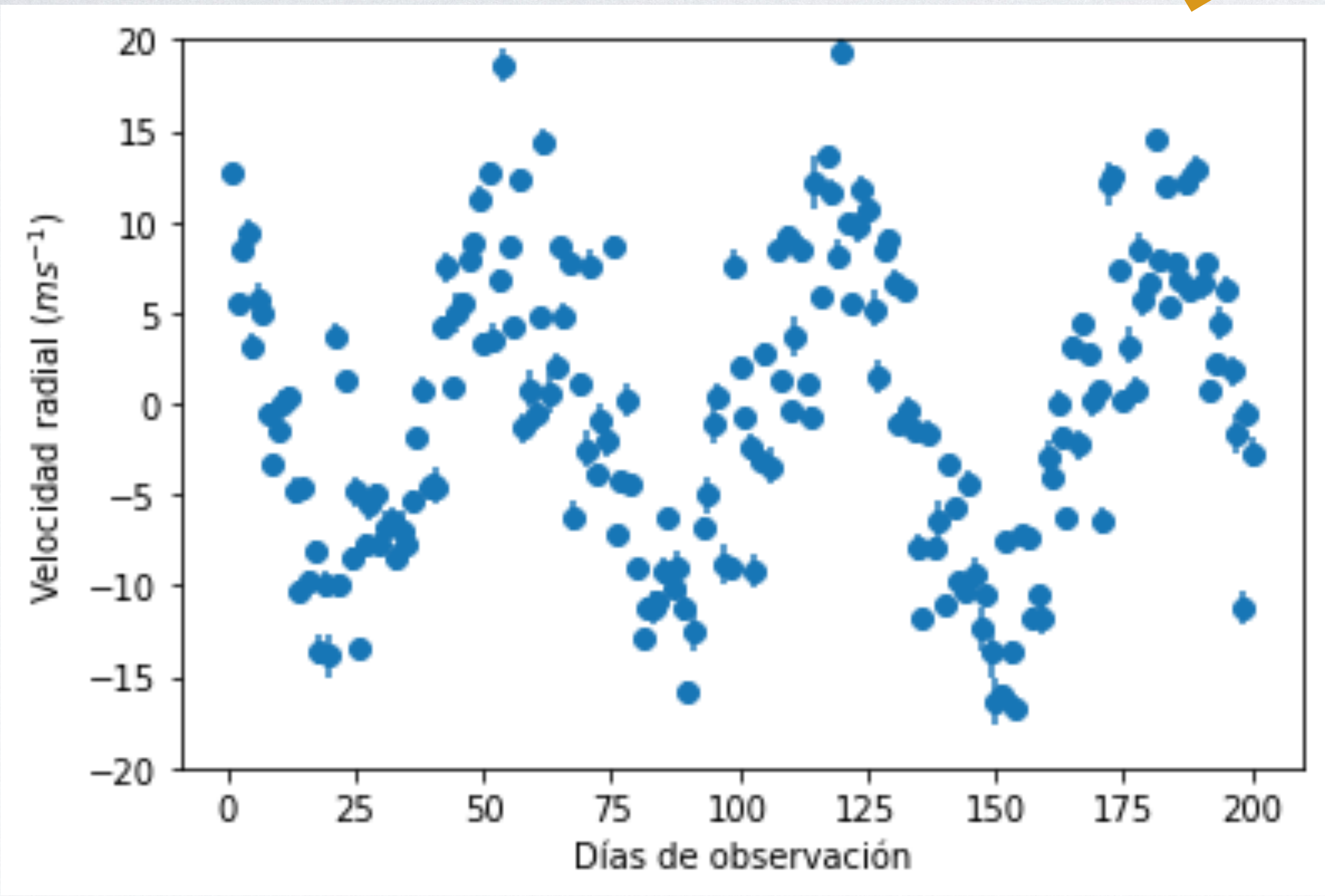

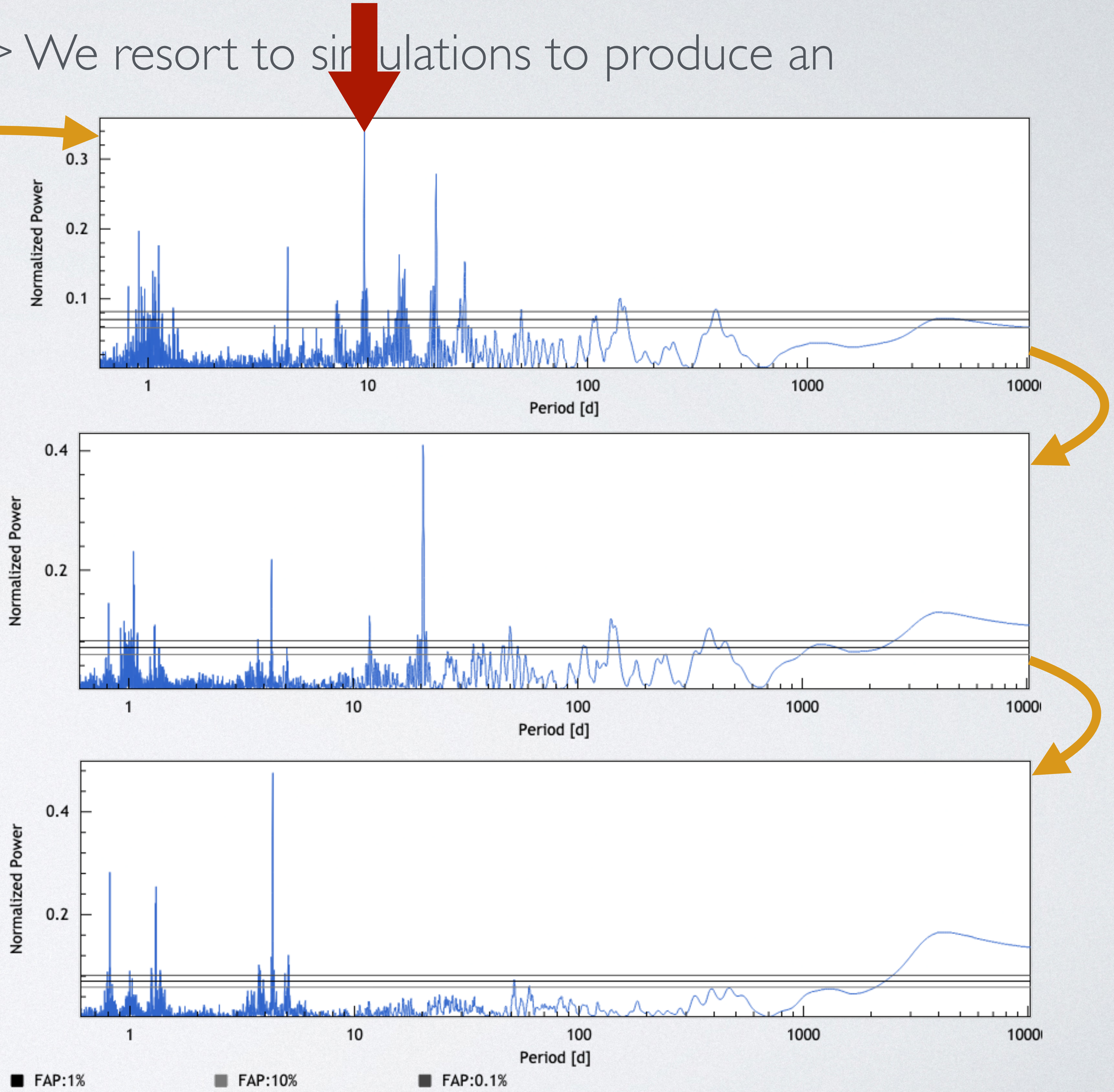

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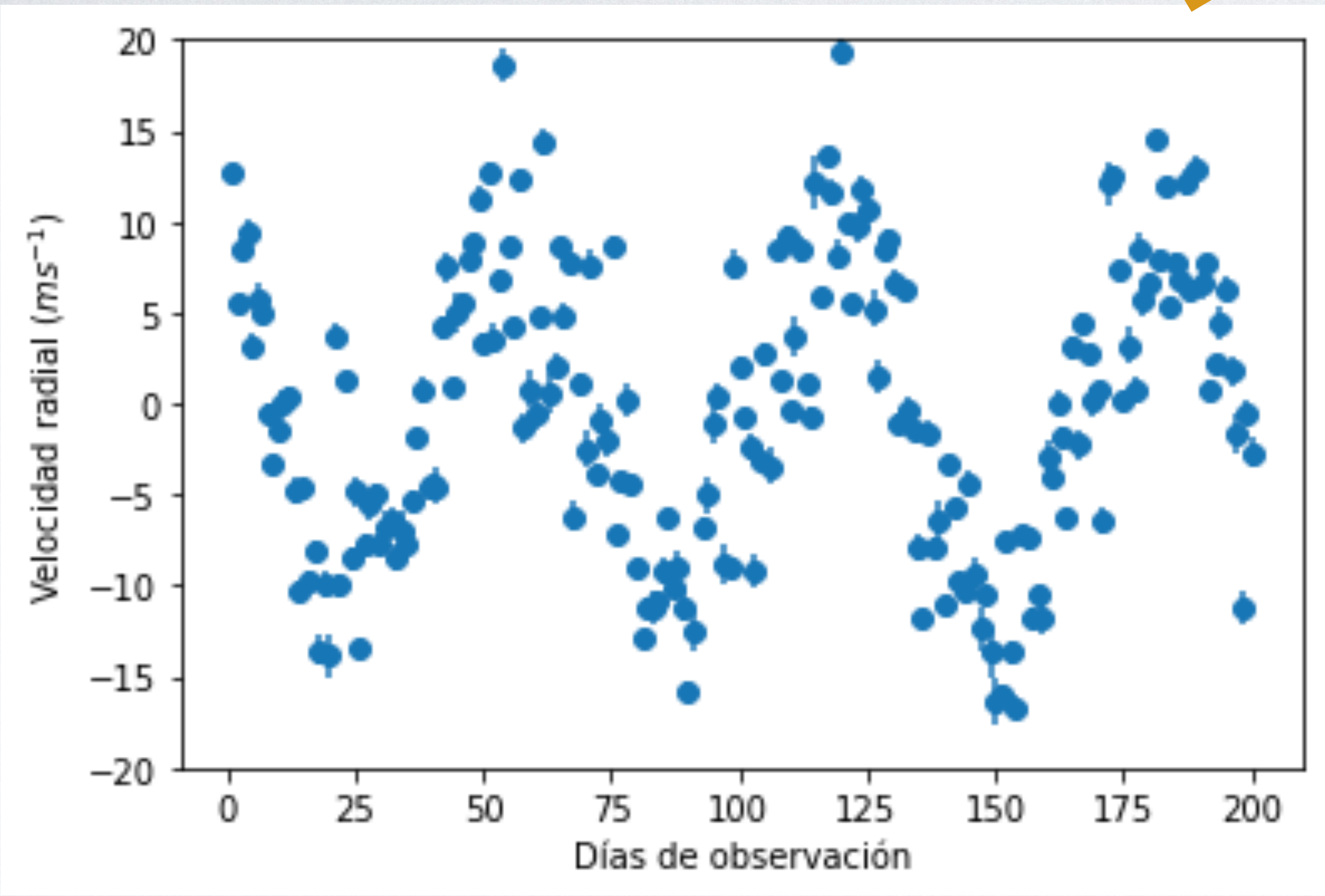

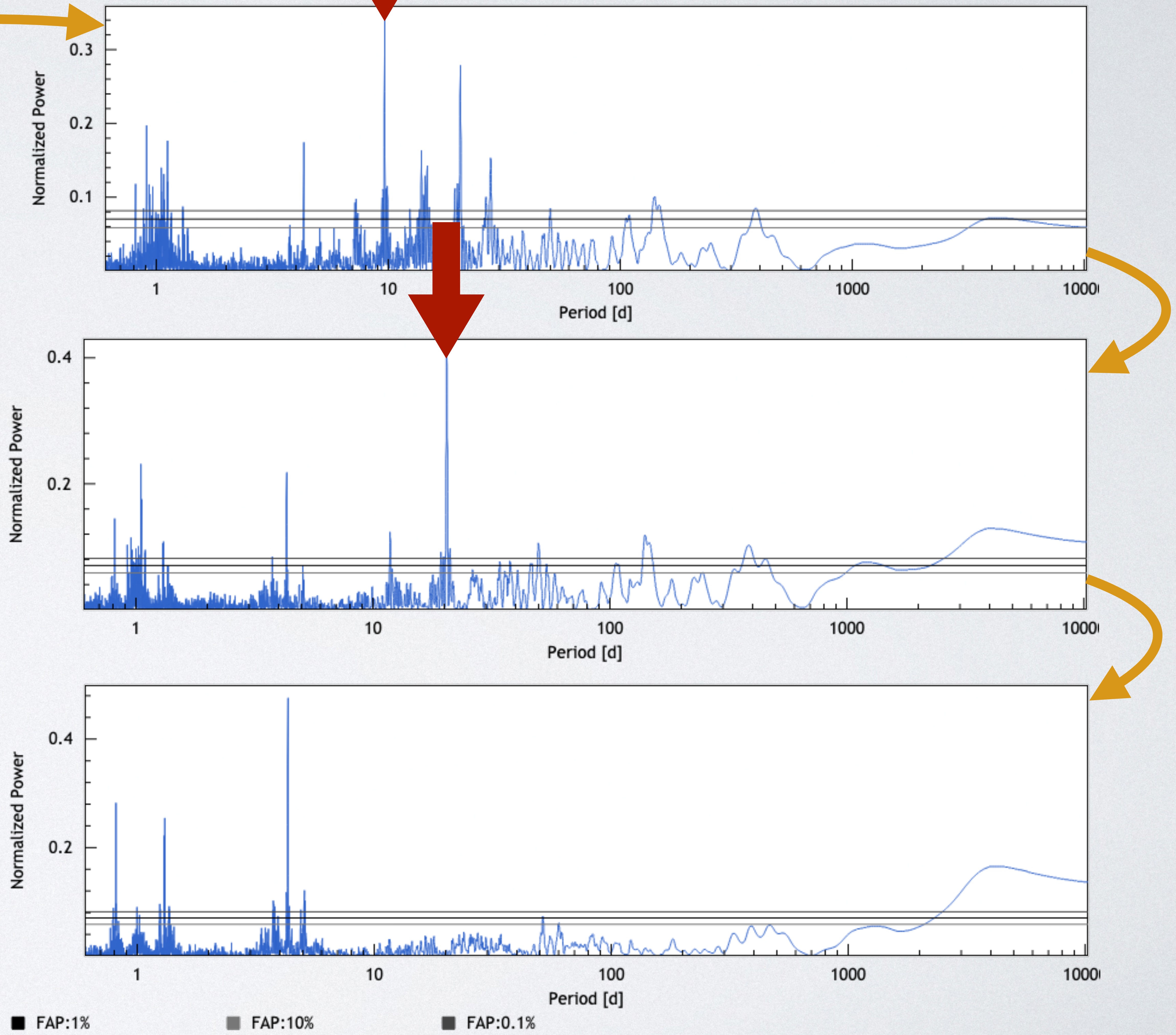

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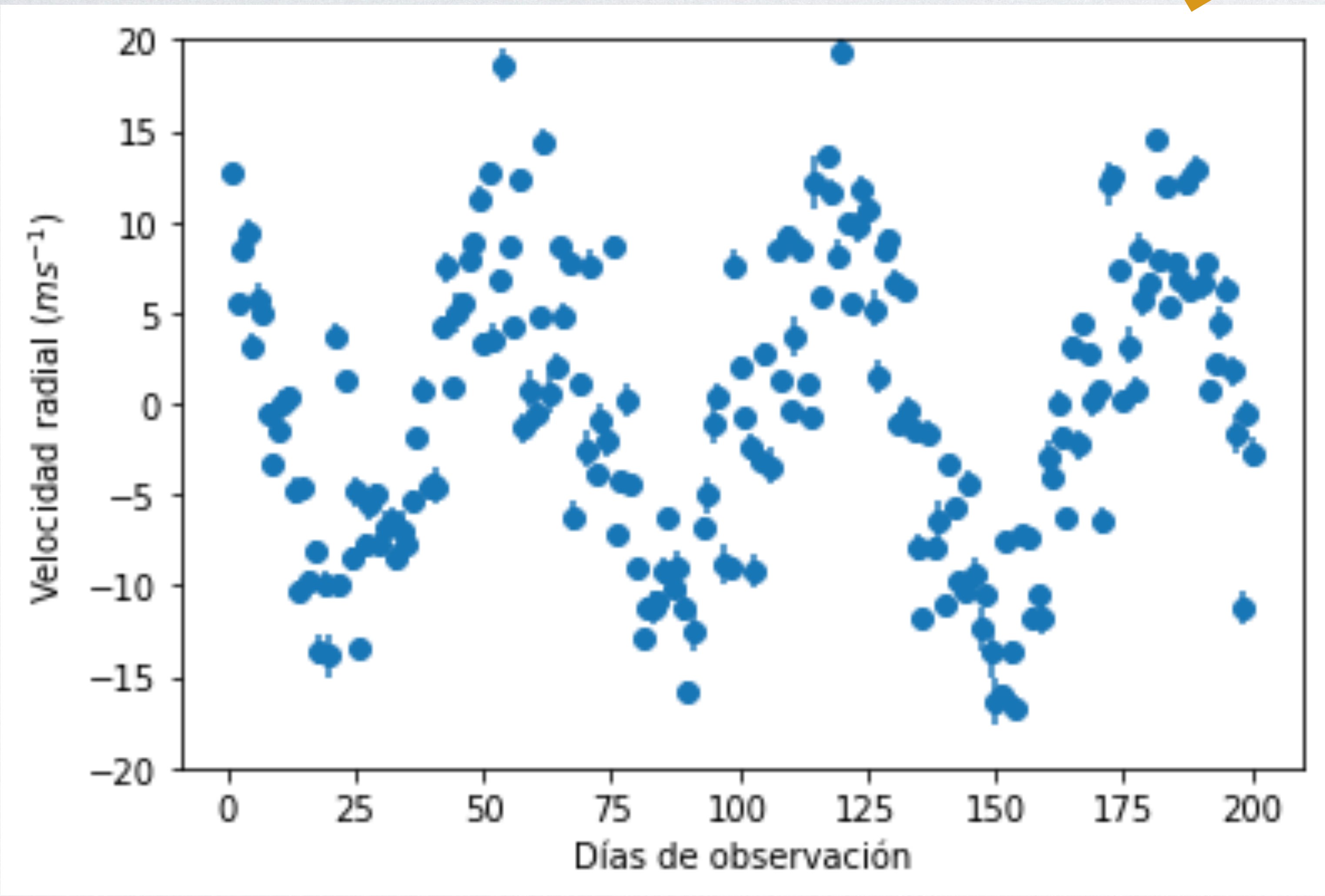
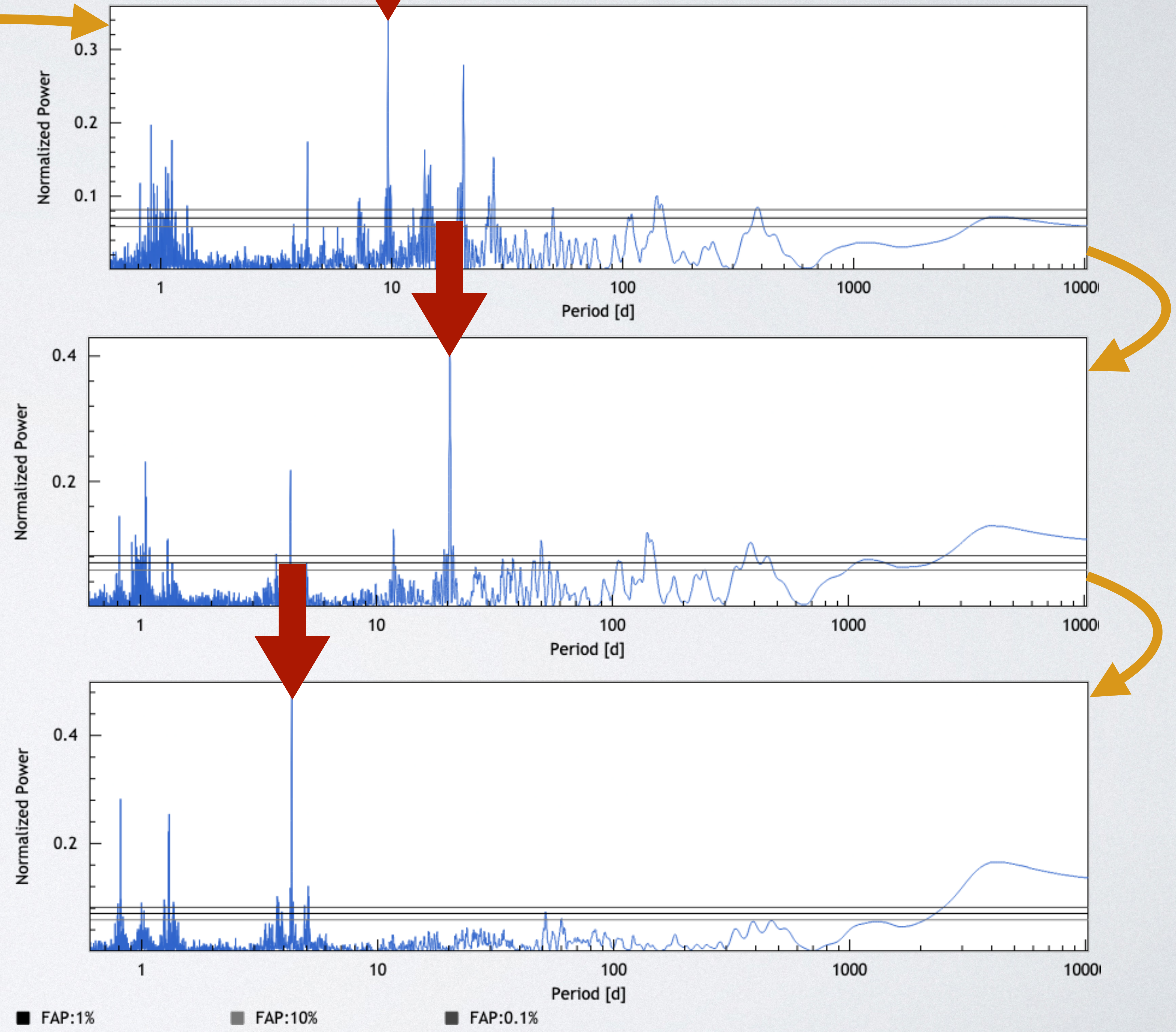
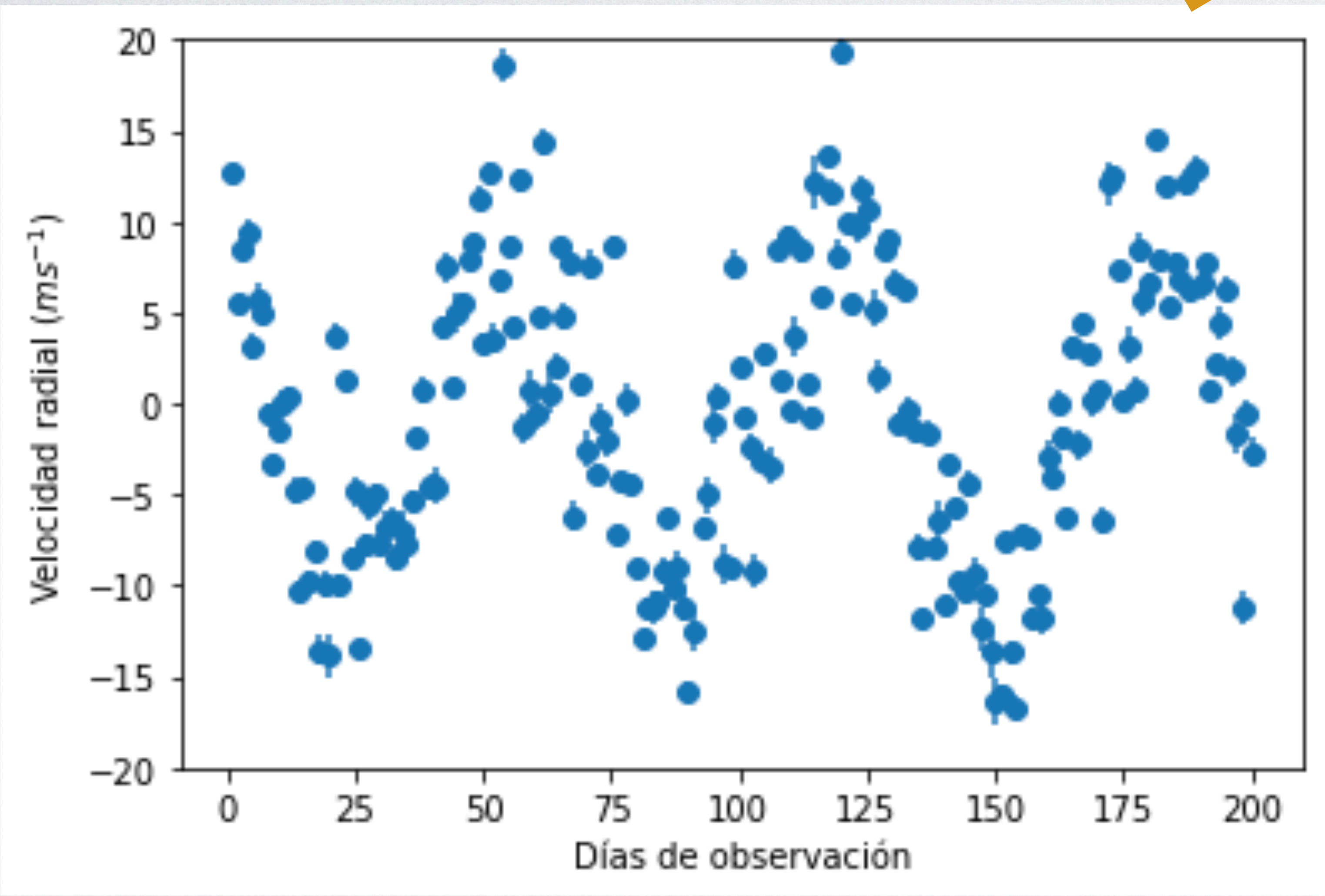
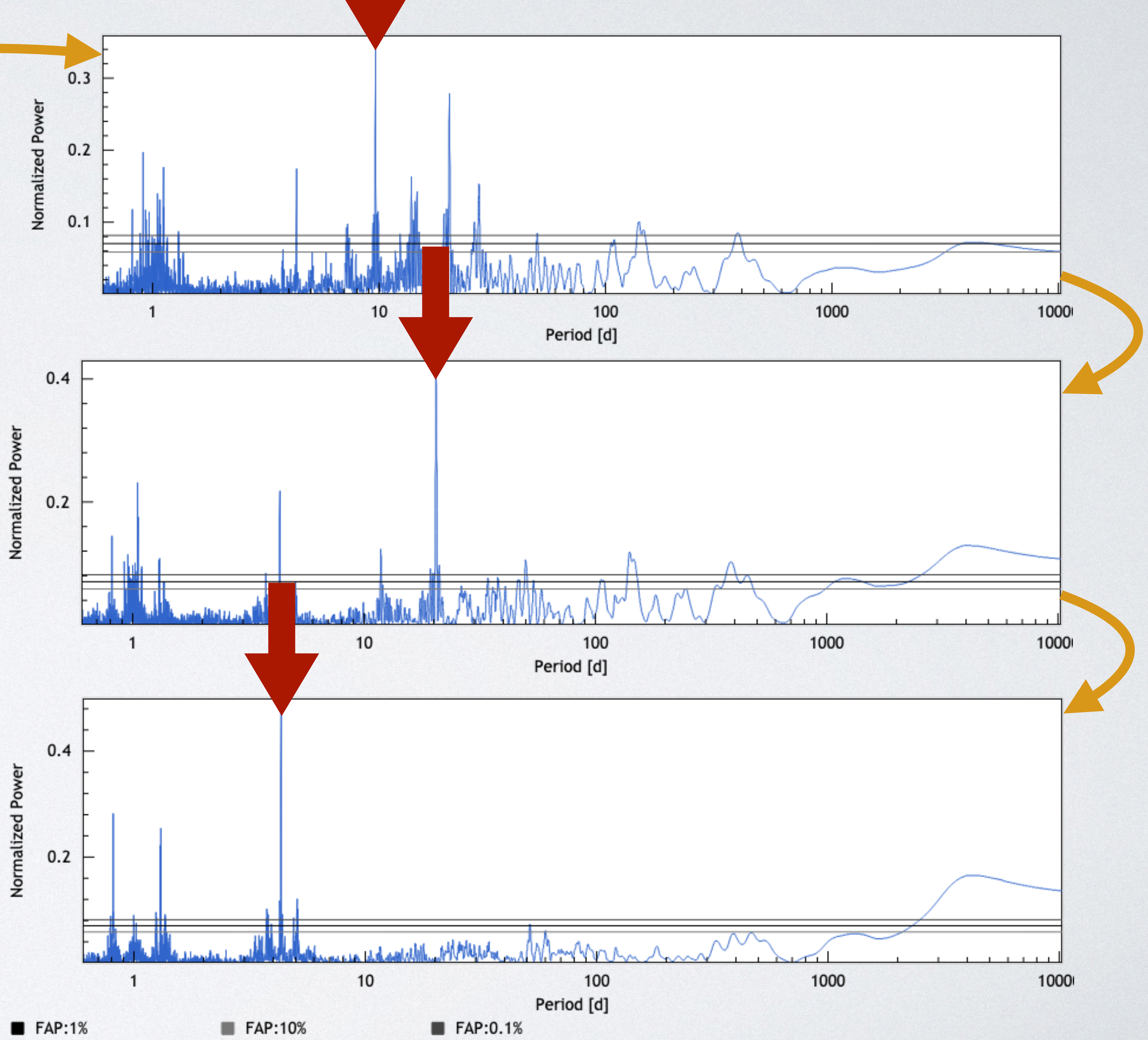




DATA

RV surveys do not provide LARGE amounts of data. —> We resort to simulations to produce an appropriate training set.





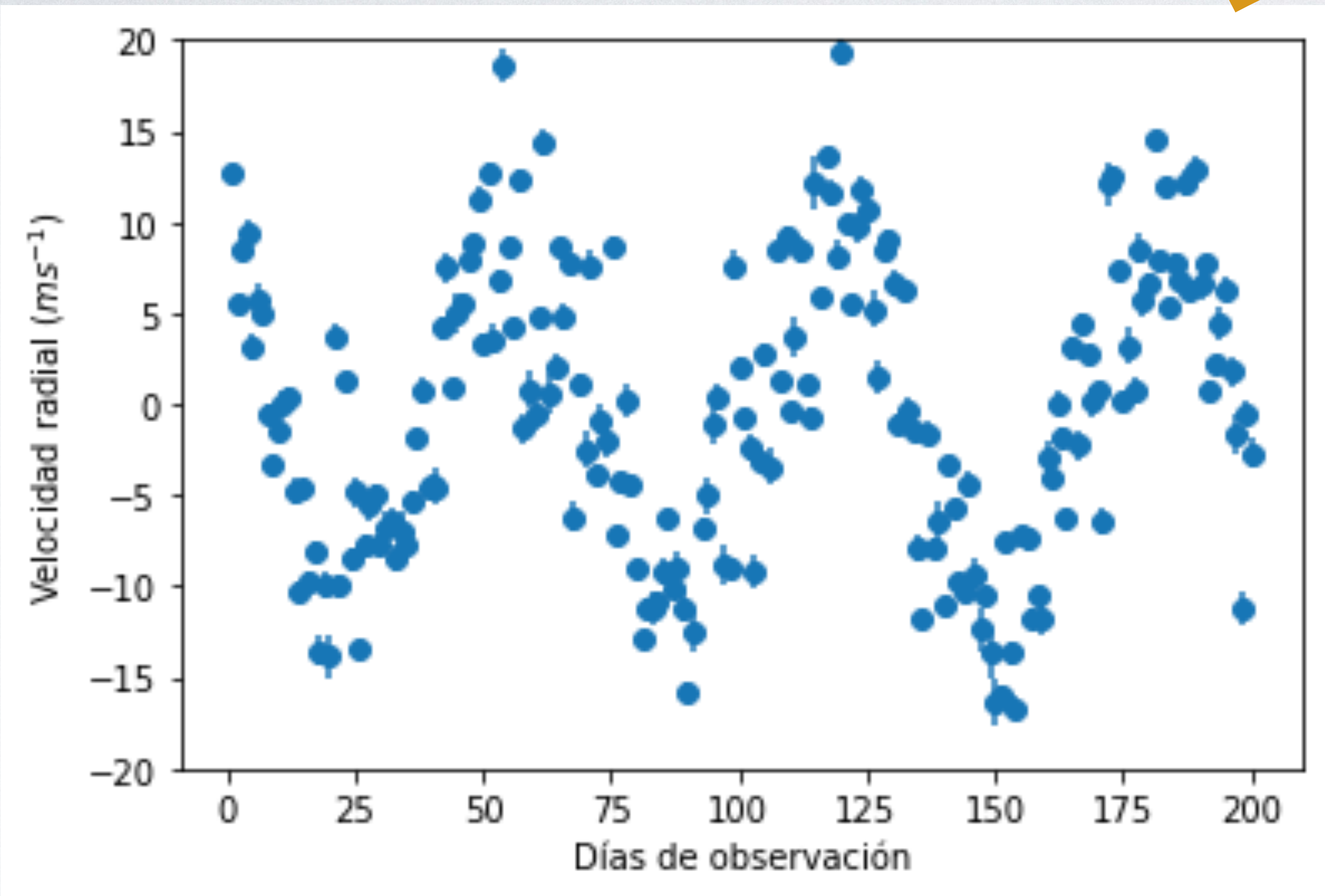
At each step: planet?

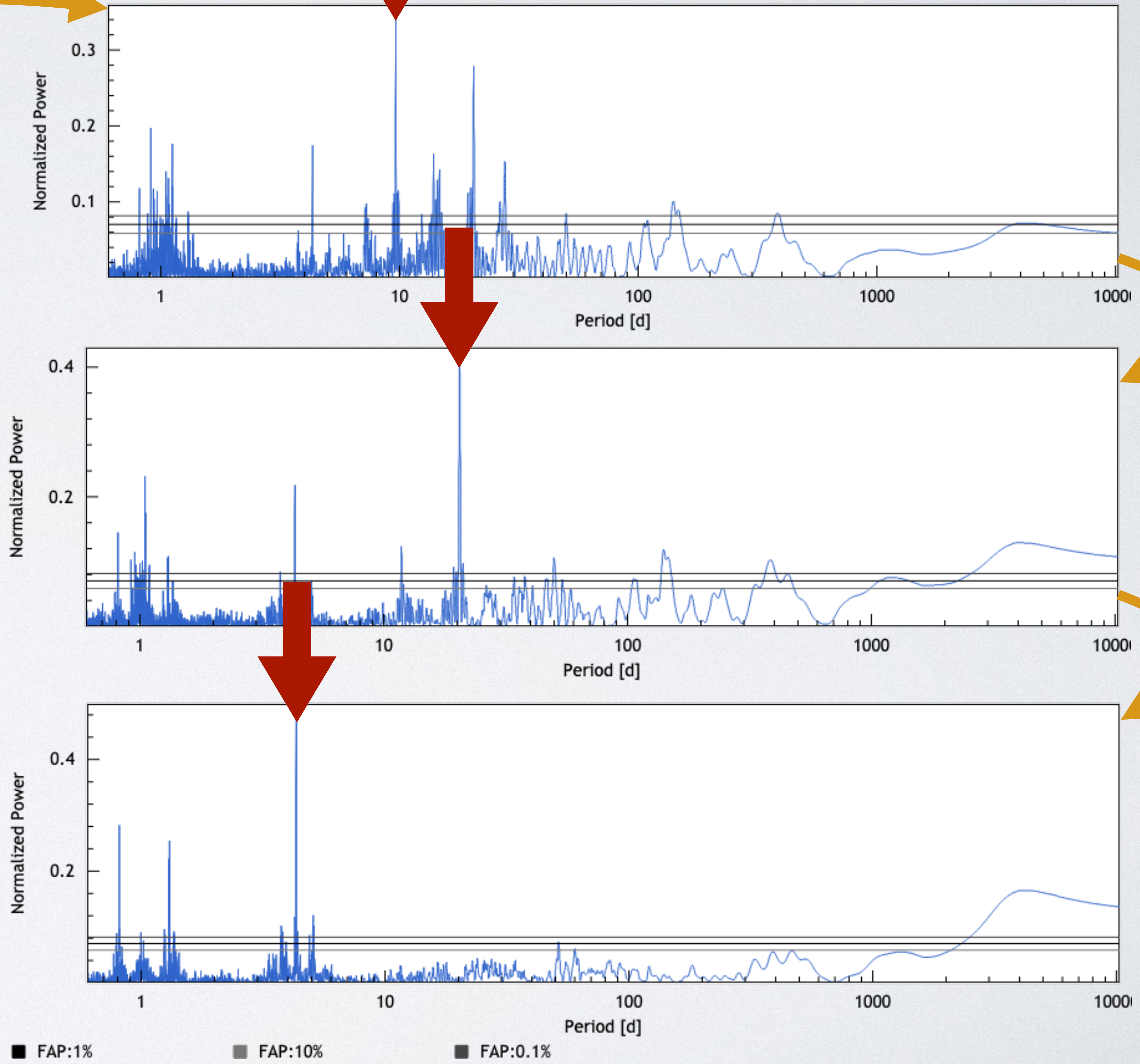
yes; *t=1*

no; *t=0*

DATA

RV surveys do not provide LARGE amounts of data. —> We resort to simulations to produce an appropriate training set.



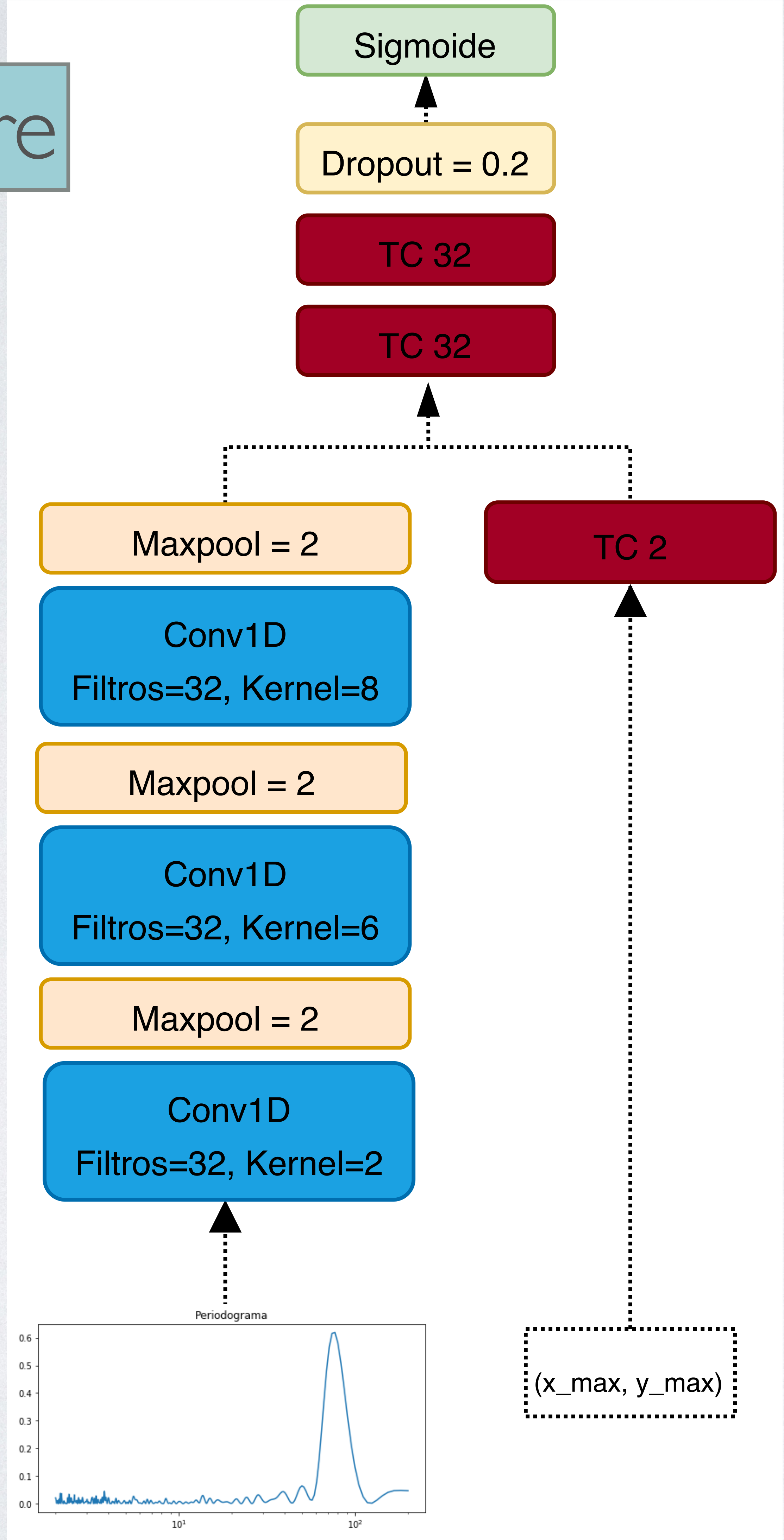


Training set: 13700 periodograms (3425 stars)
Unbalanced: around 40% of positive cases.

Test sets (2):
2500 stars (1e4 GLS) + 5000 stars (2e4 GLS)

OUR ML MODEL

Architecture



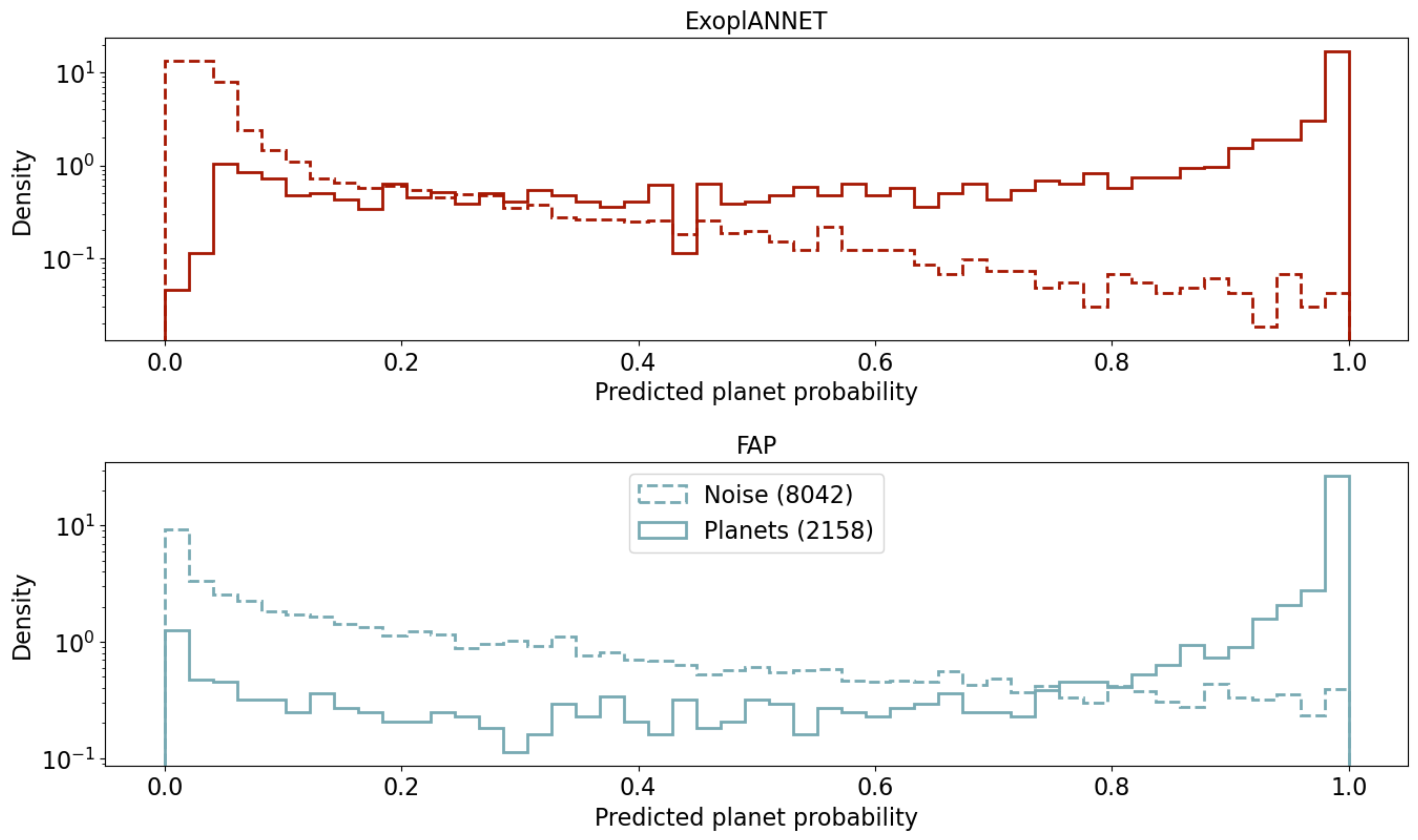
- implemented in `Tensorflow / Keras`
- reLU activation functions

Training

- binary crossentropy loss function.
- Adam optimiser
- batch size = 16

Name….

Predicted probabilities



$$\text{precisión} = \frac{TP}{TP + FP}$$

$$\text{recall} = \text{exhaustividad} = \frac{TP}{TP + FN}$$

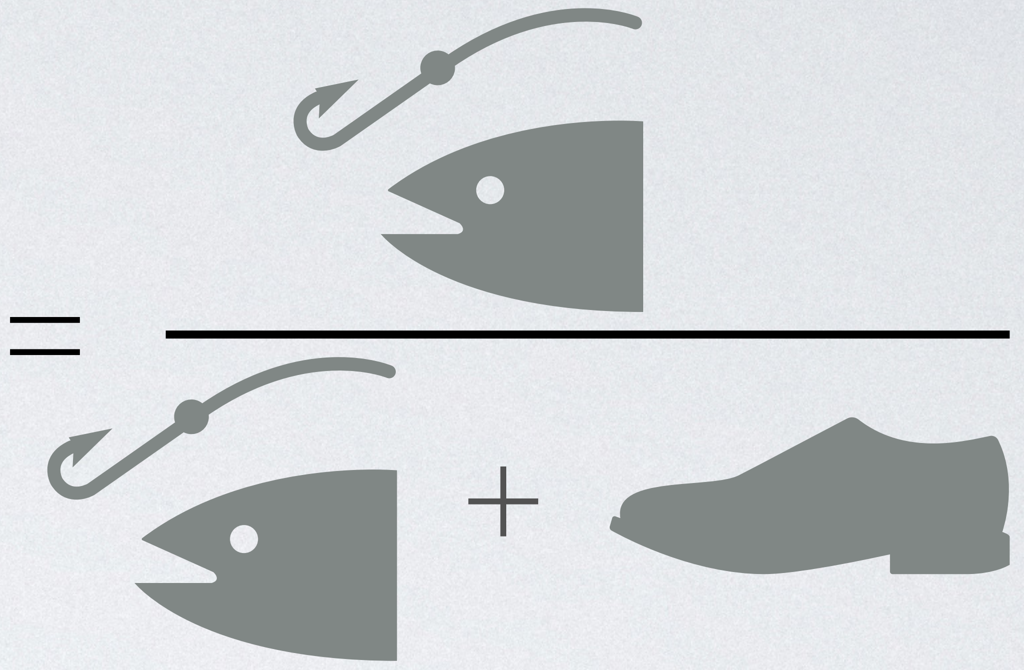
$$\text{precisión} = \frac{TP}{TP + FP}$$

instances classified as positive (planets)

$$\text{recall} = \text{exhaustividad} = \frac{TP}{TP + FN}$$

true positive instances

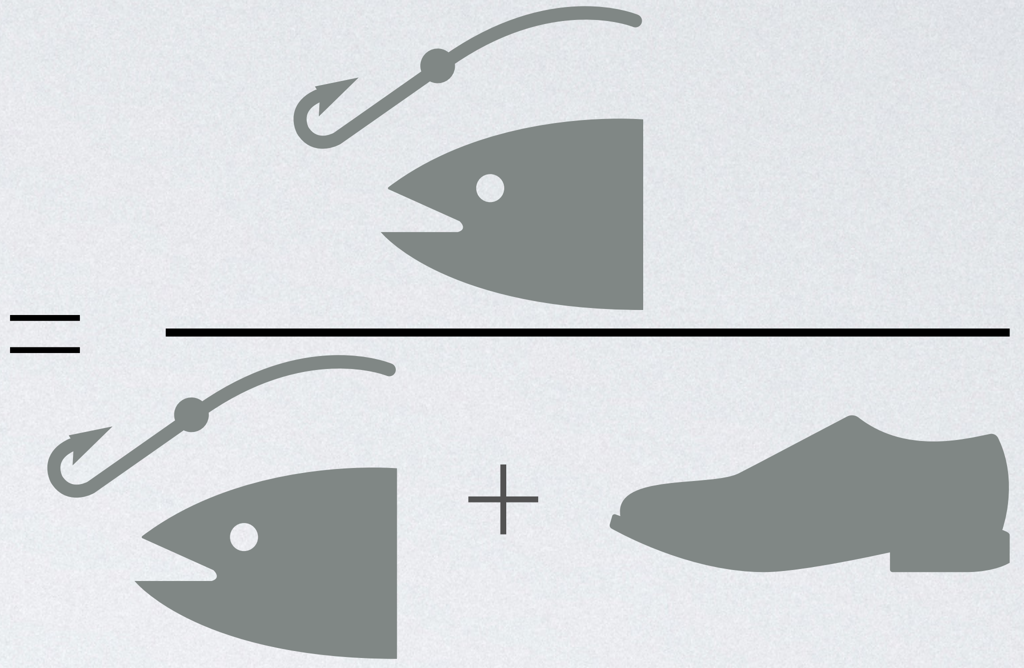
$$\text{precisión} = \frac{TP}{TP + FP} =$$



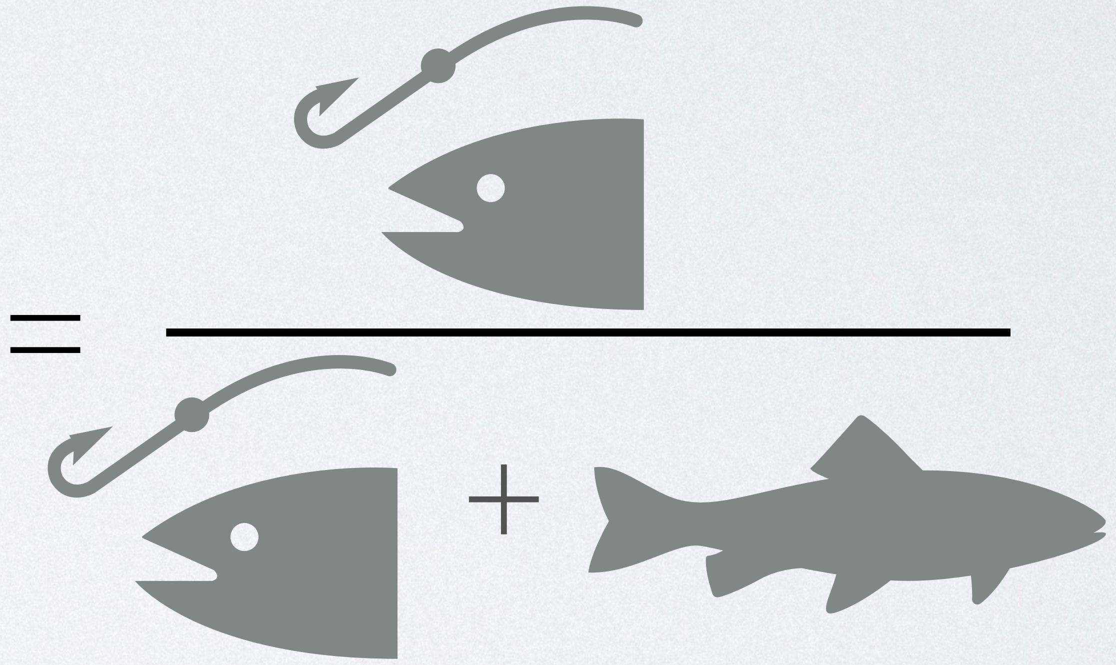
$$\text{recall} = \text{exhaustividad} = \frac{TP}{TP + FN}$$

true positive
instances

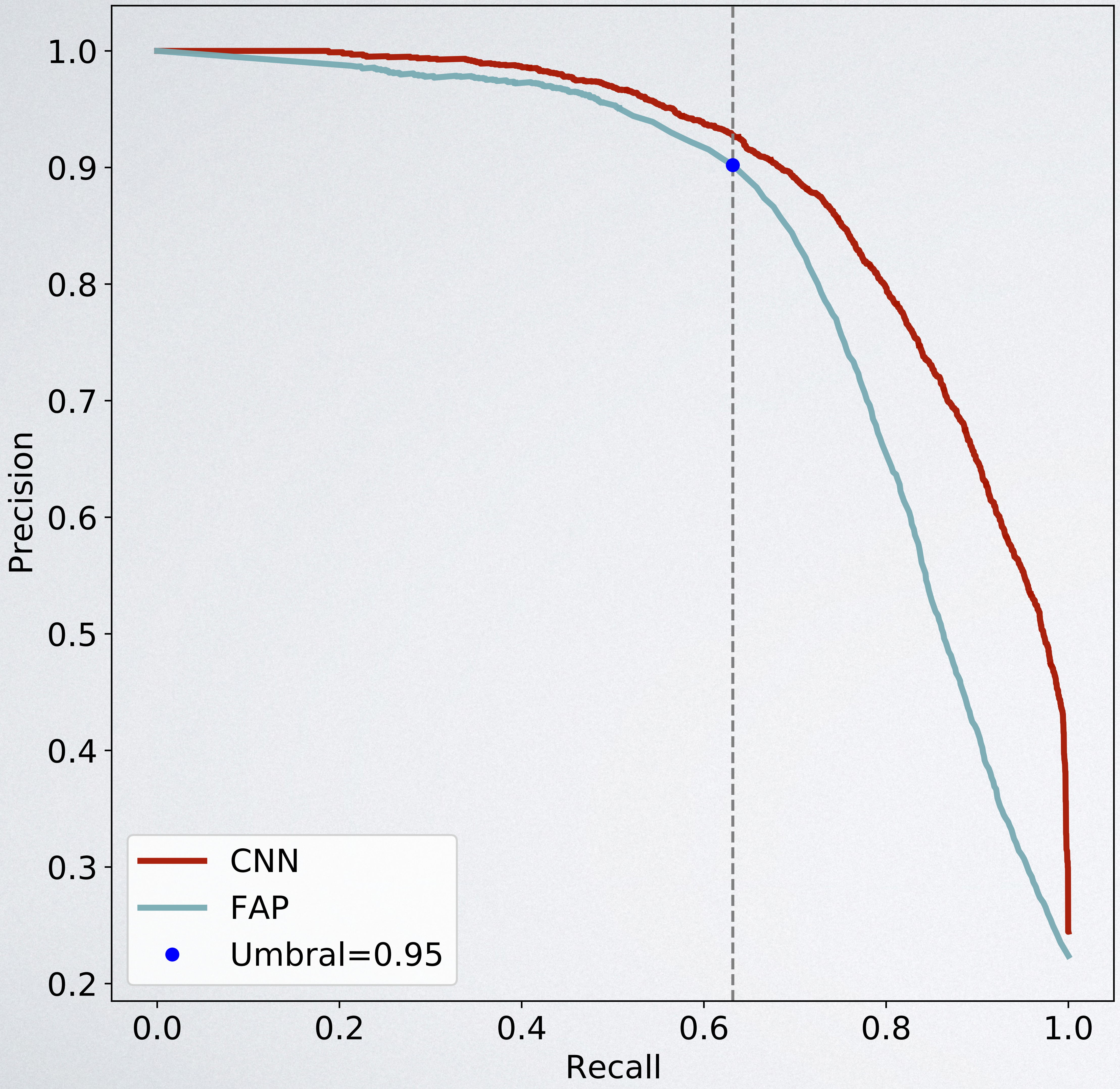
$$\text{precisión} = \frac{TP}{TP + FP} =$$

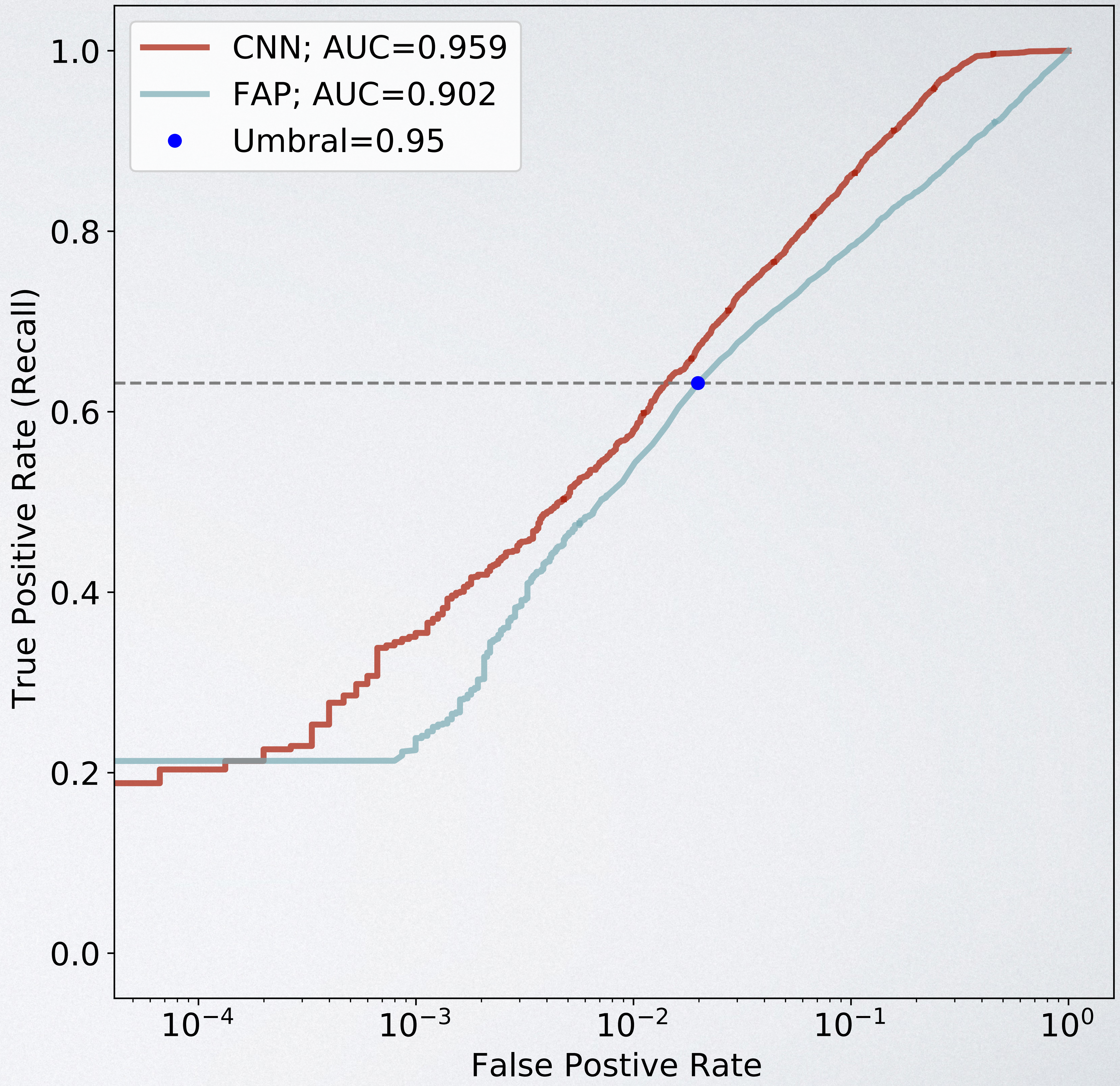


$$\text{recall} = \text{exhaustividad} = \frac{TP}{TP + FN} =$$

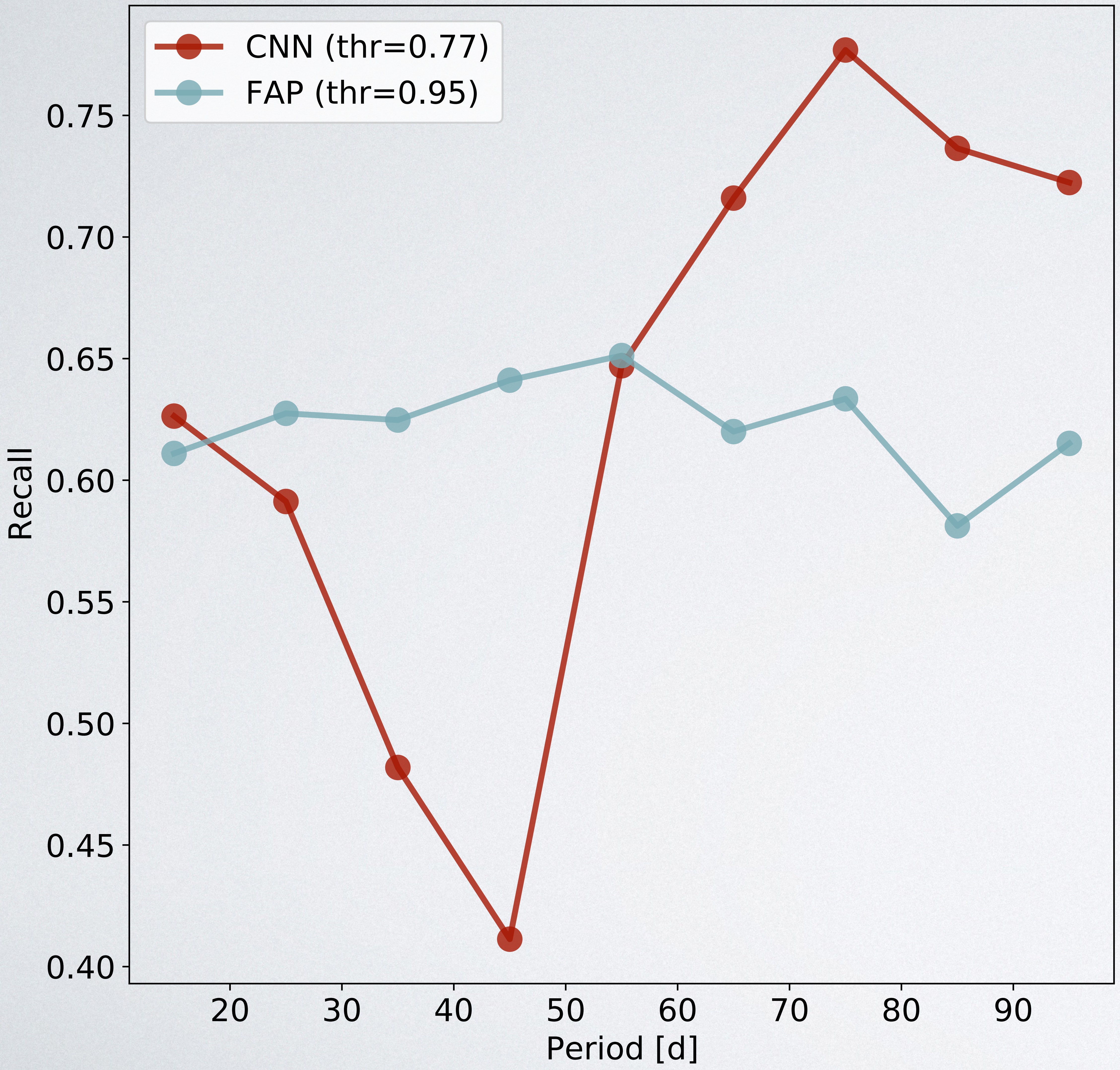


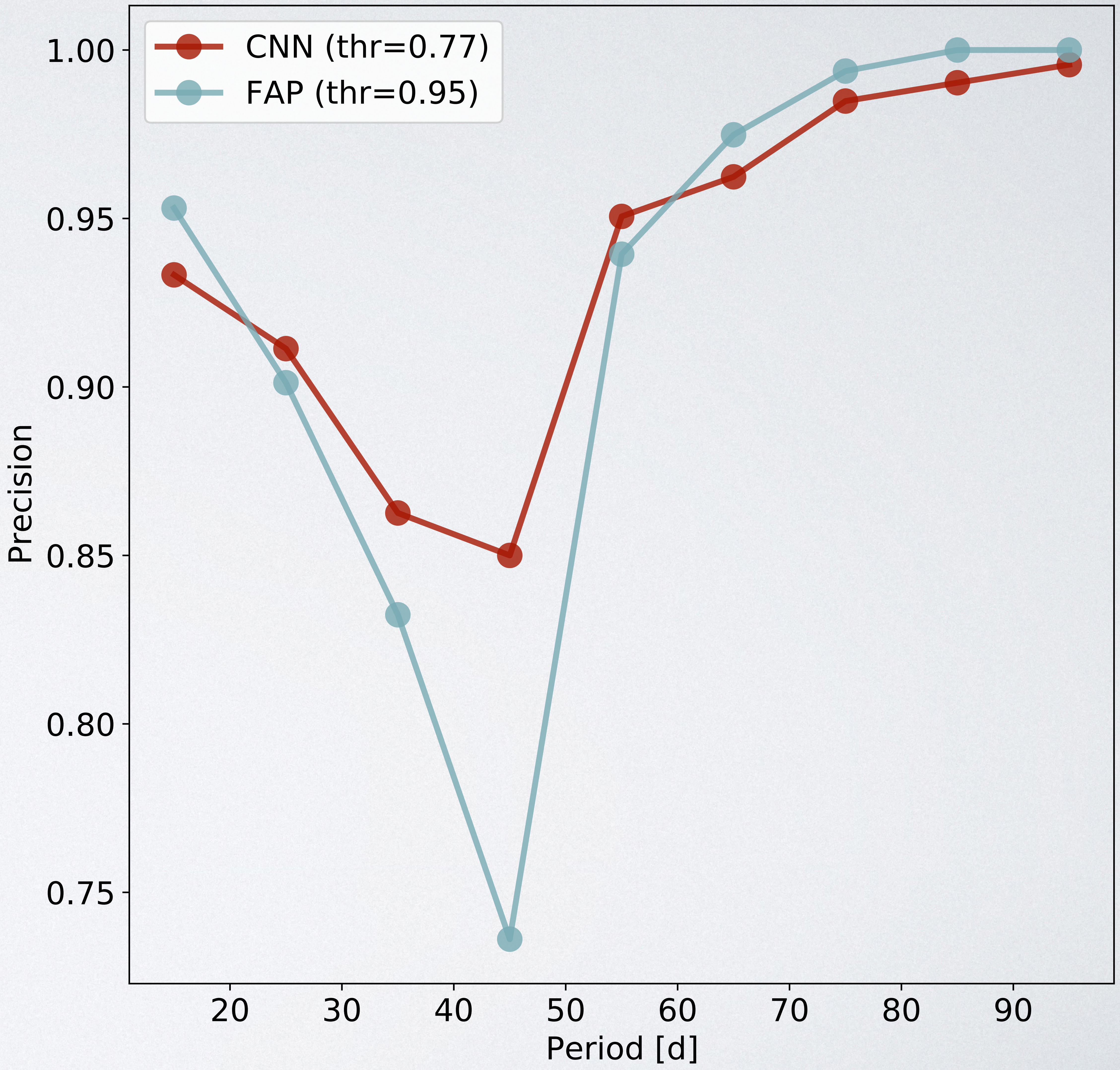
ExoplANNet outperforms traditional method (FAP)



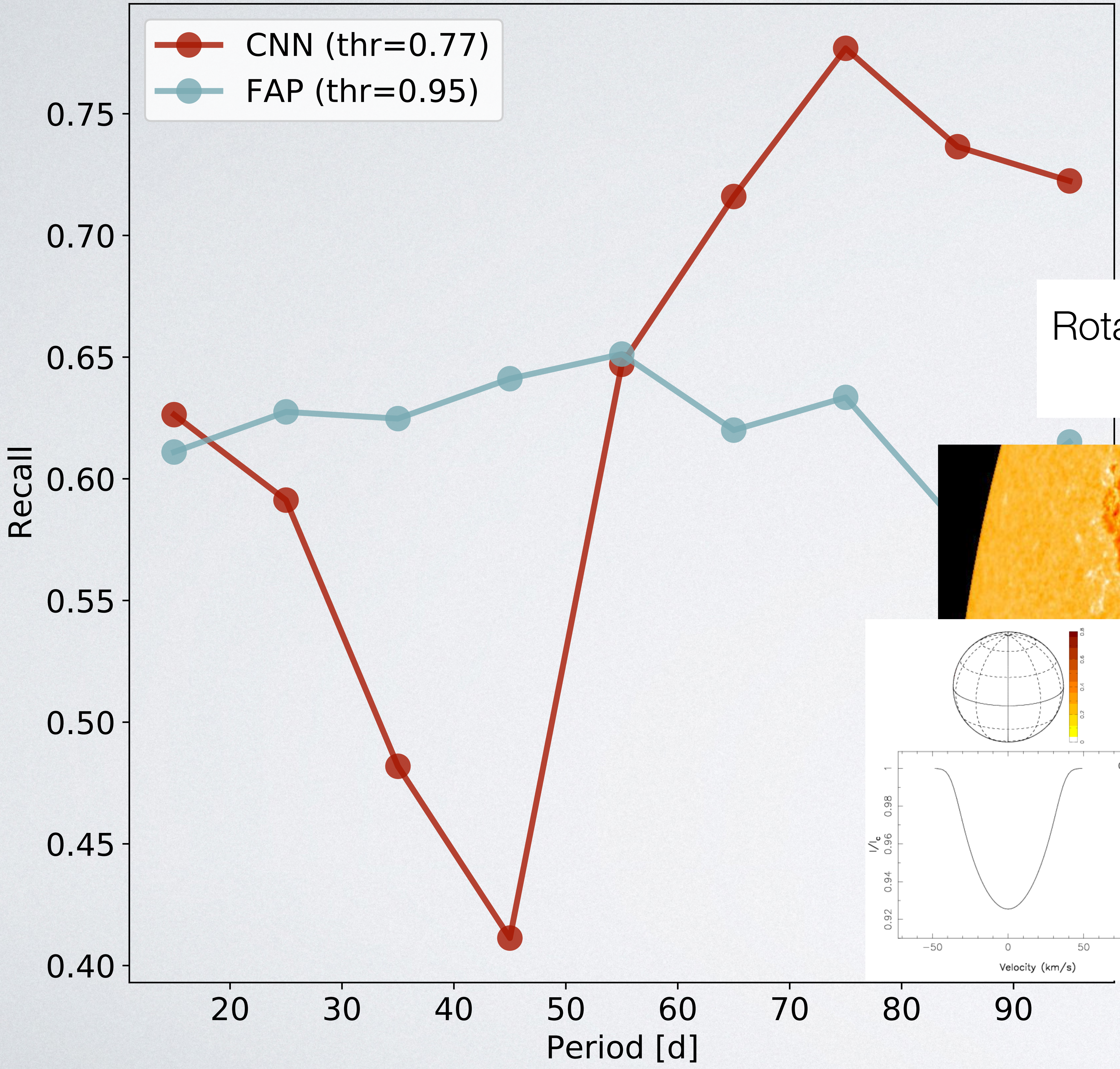


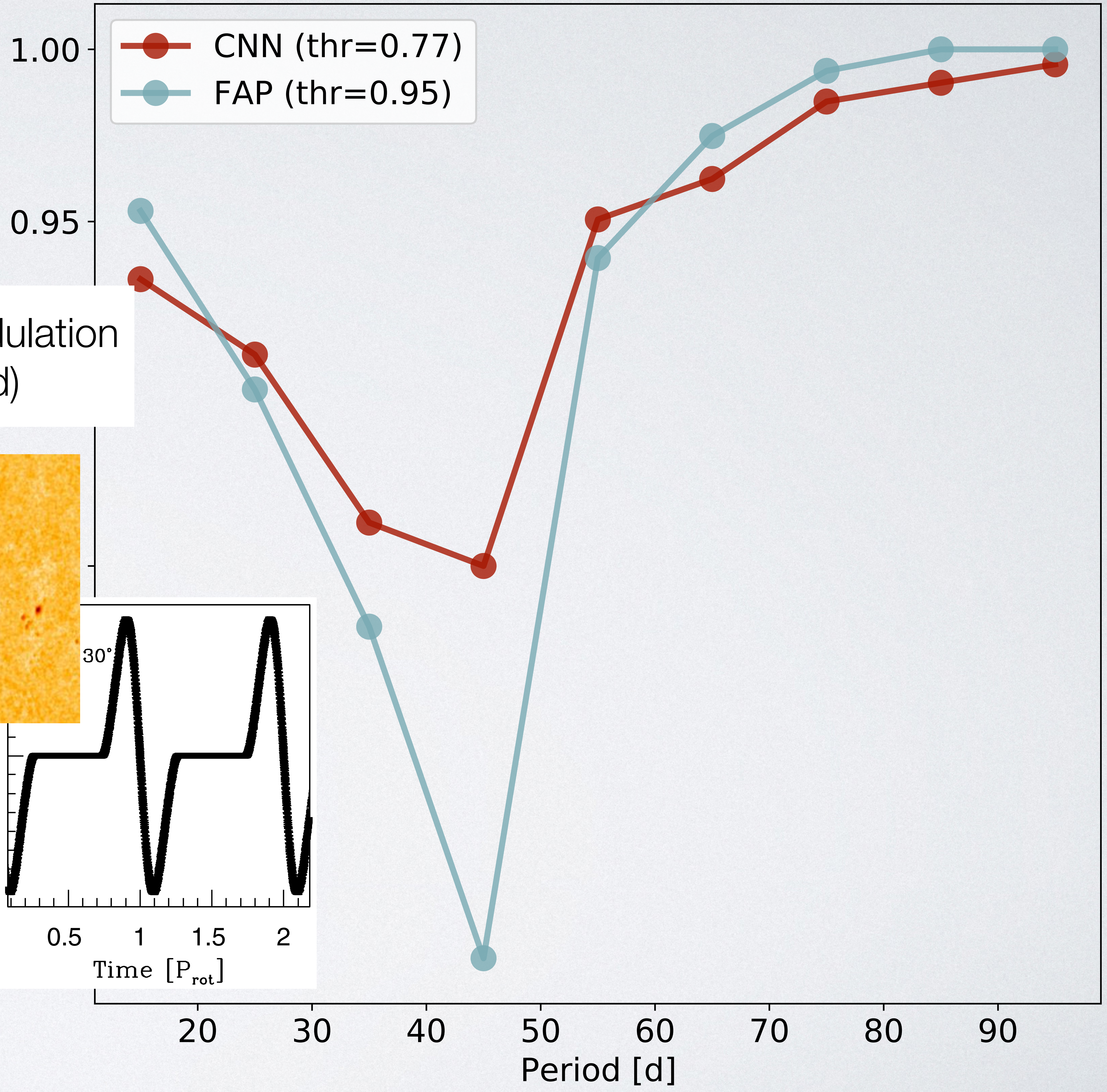
Dependence with data input parameters



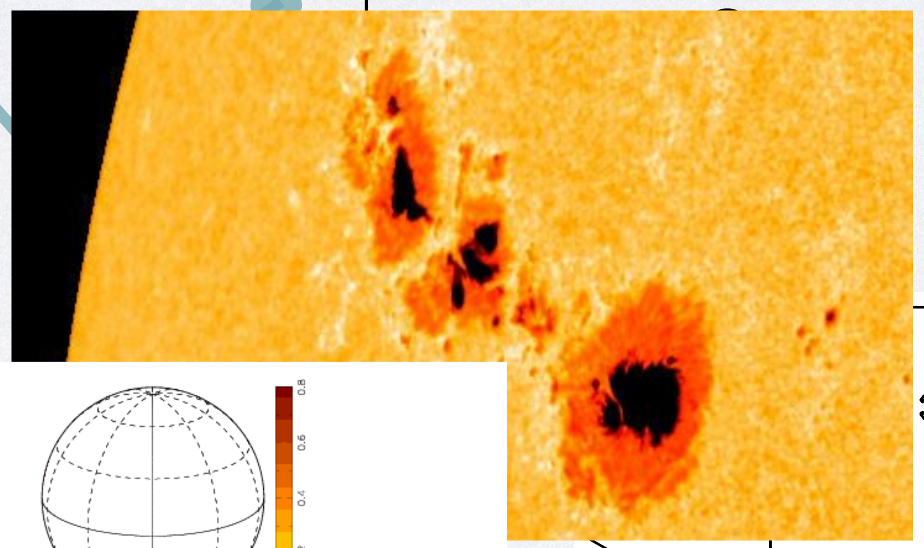


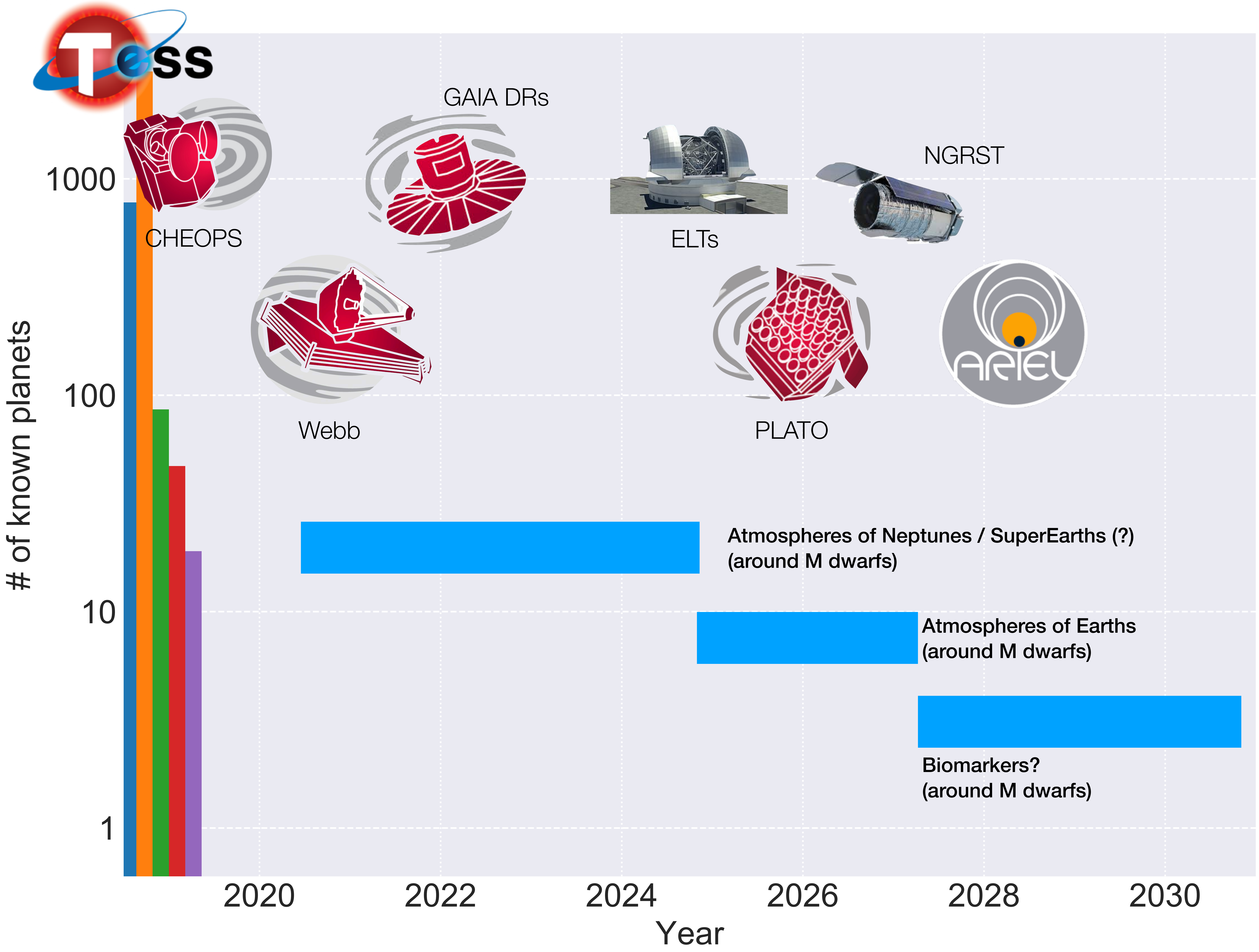
Is ExoplANNet avoiding problems close to the rotational period?





Rotational modulation
(10 - 50 d)





GAIA DRs
NGRST
1000
CHEOPS
ELTs
100
Webb
PLATO
# of known planets
Atmospheres of Neptunes / SuperEarths (?)
(around M dwarfs)
10
Atmospheres of Earths
(around M dwarfs)
Biomarkers?
(around M dwarfs)
1
2020
2022
2024
2026
2028
2030
Year

SUMMARY

- The last 25 years brought a wealth of information about planets outside the Solar system.
- Many questions remain open. Chief among them, is the occurrence of planets like Earth.
- Our exoplanet team at UNSAM uses data science and machine learning techniques to solve some of the outstanding questions in exoplanet science, by improving instrument performance, operation efficiency and / or detection power.