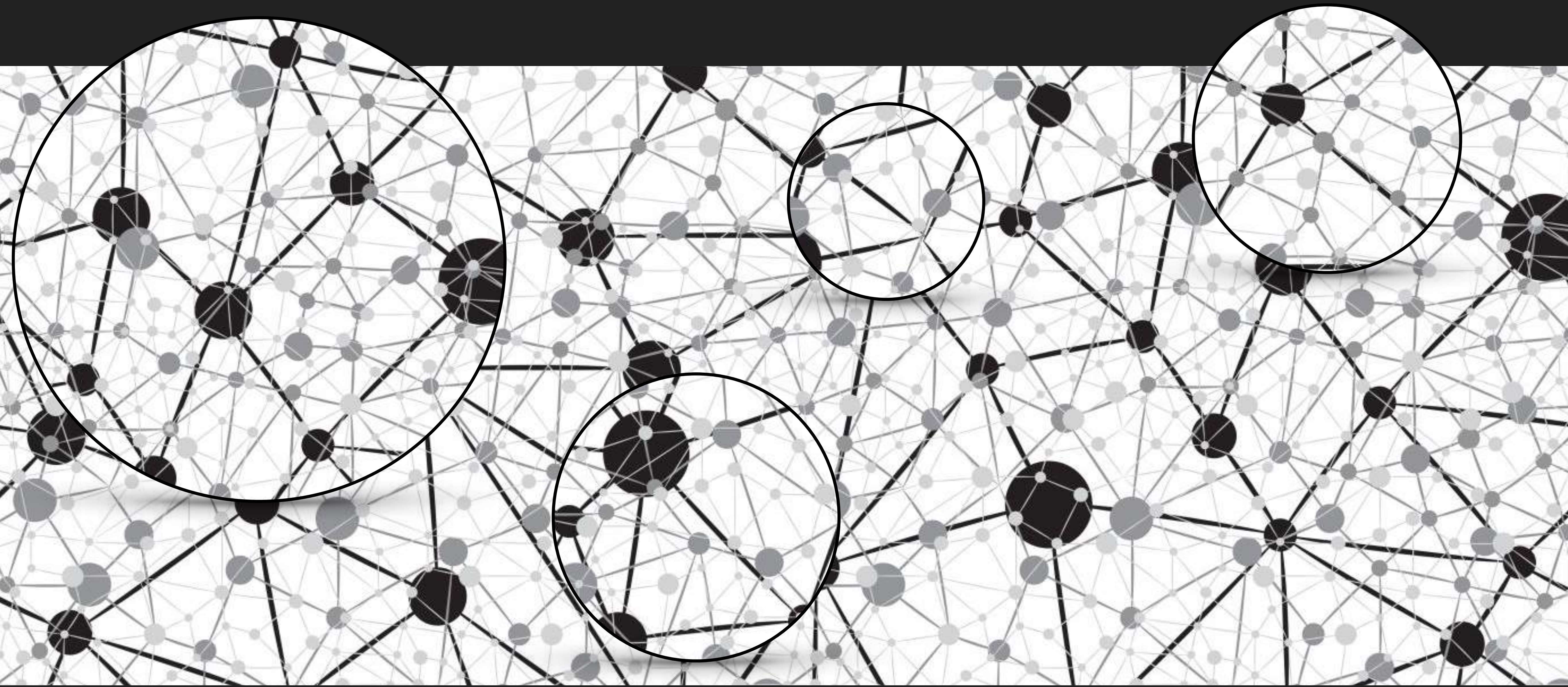
Filling in the gaps:

Imputing exoplanet properties with machine learning



Elizabeth Tasker JAXA

Nicholas Guttenberg

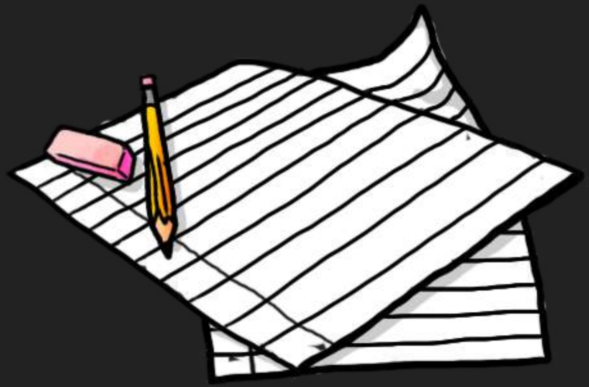
EARTH - LIFE SCIENCE INSTITUTE

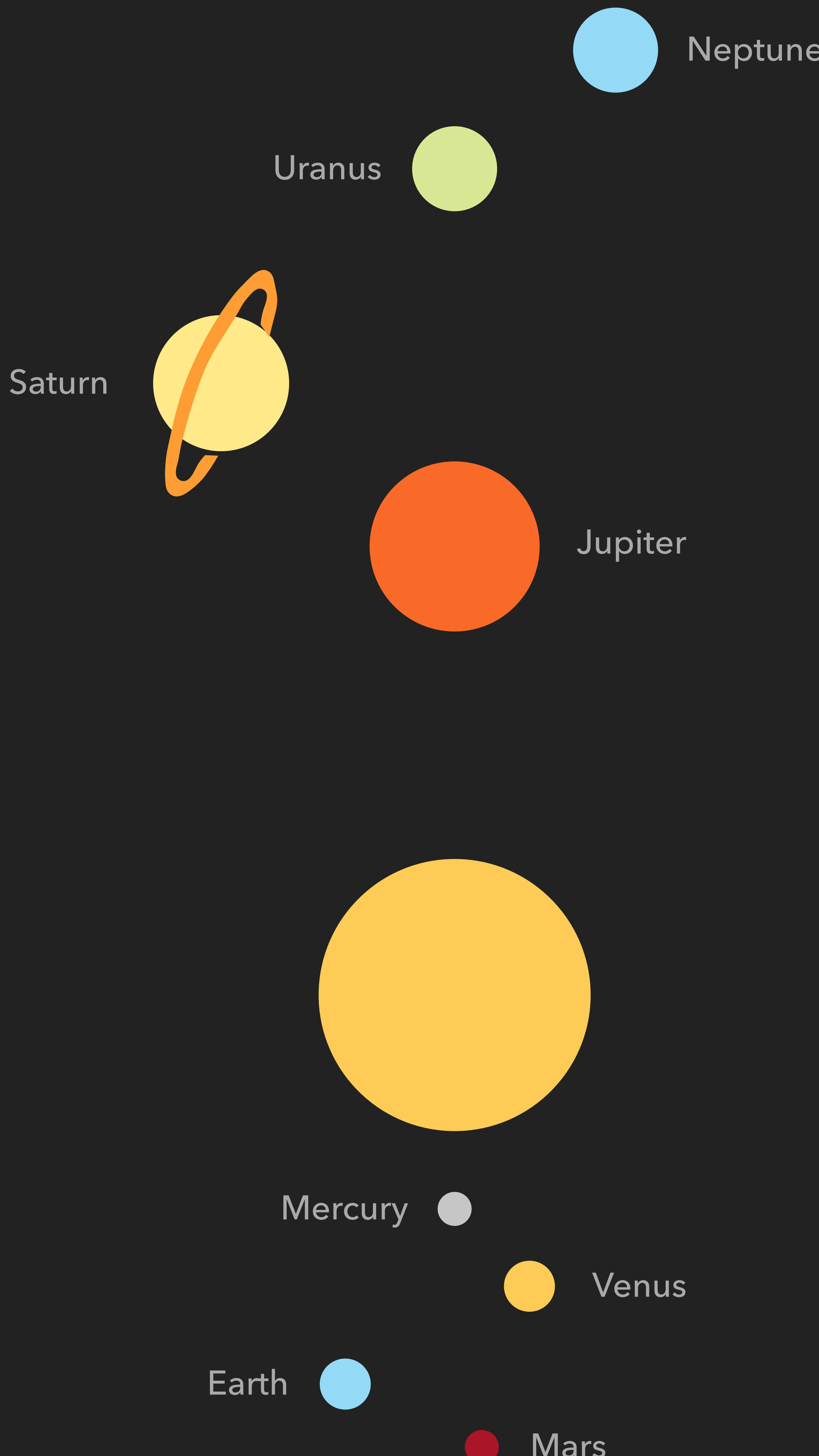
Matthieu Laneuville

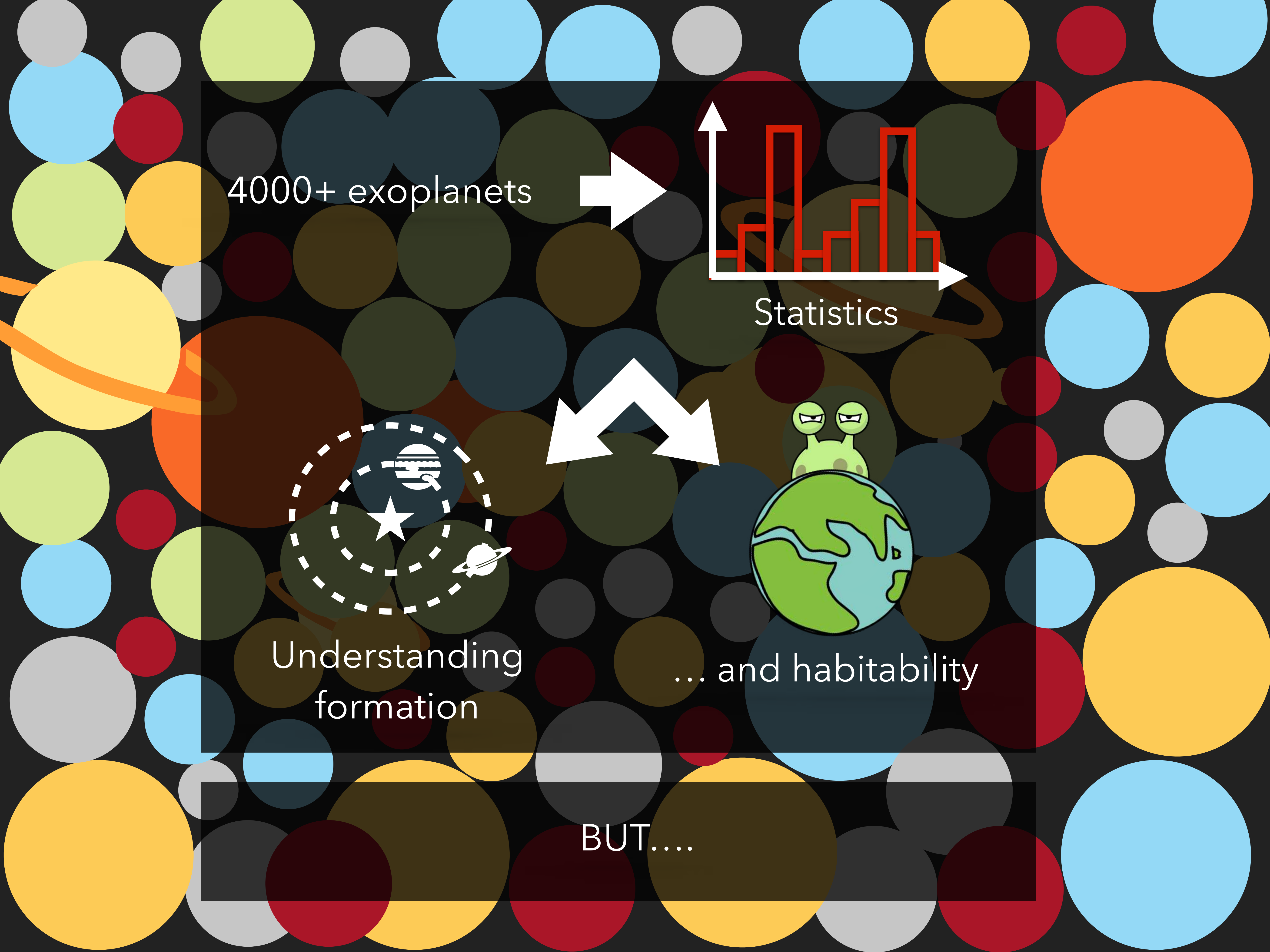
EARTH - LIFE SCIENCE INSTITUTE

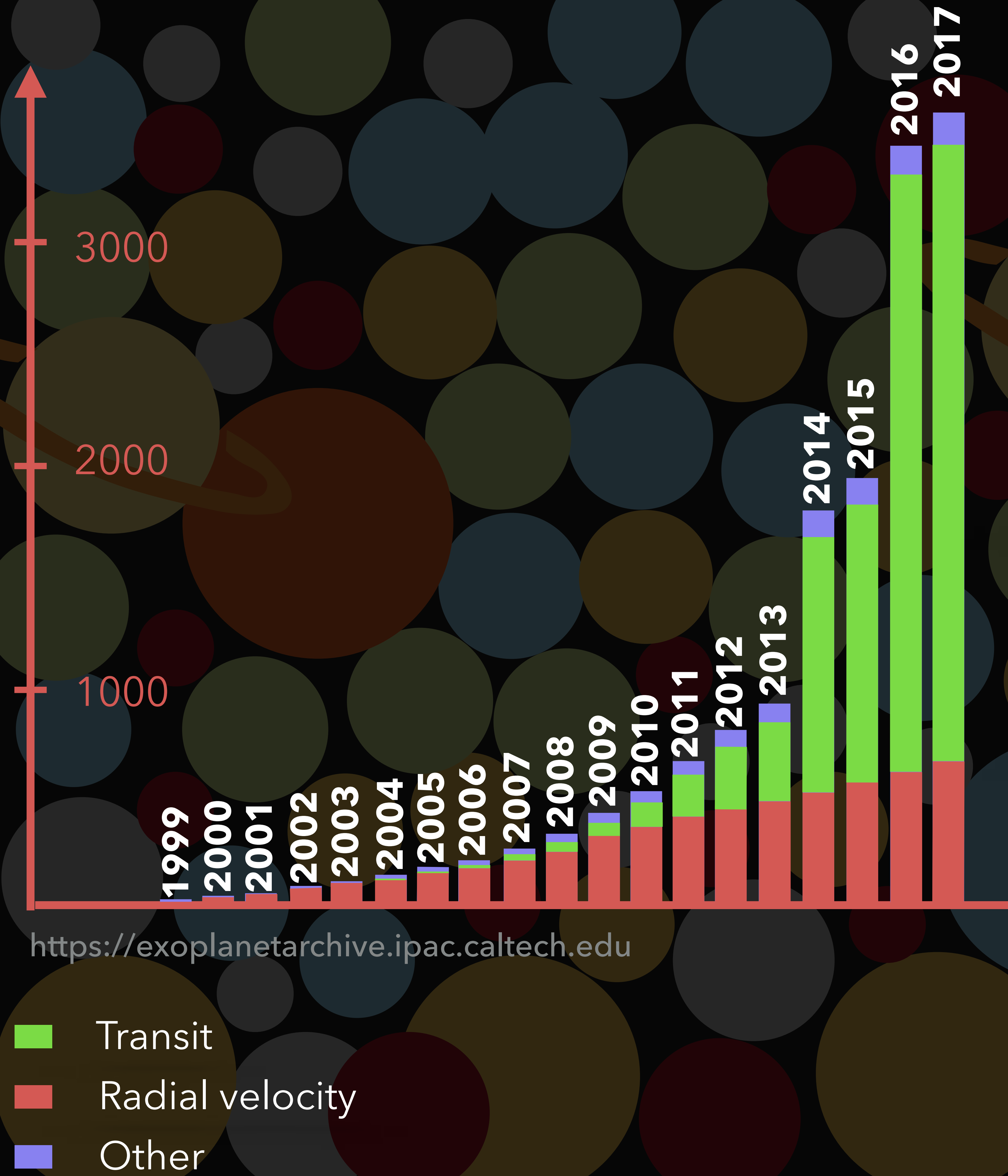
Tasker, Laneuville & Guttenberg, AJ 2020.

ArXiv: 1911.11035




Neptune
Uranus
Saturn
Jupiter
Mercury
Venus
Earth
Mars

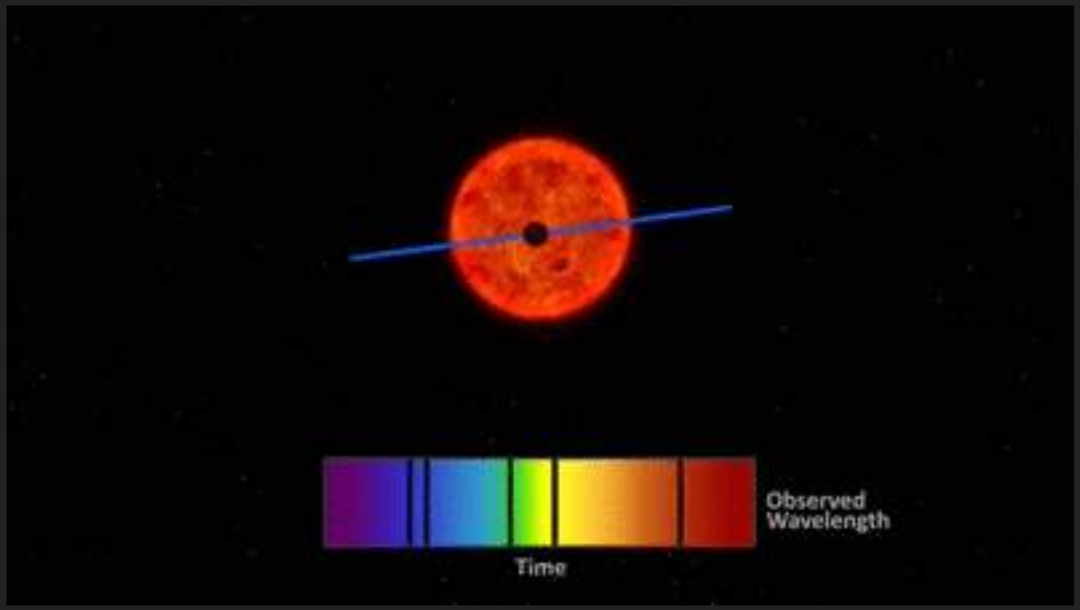

4000+ exoplanets
Statistics
Understanding
formation
… and habitability
BUT….



96% exoplanets found by either the radial velocity or transit technique

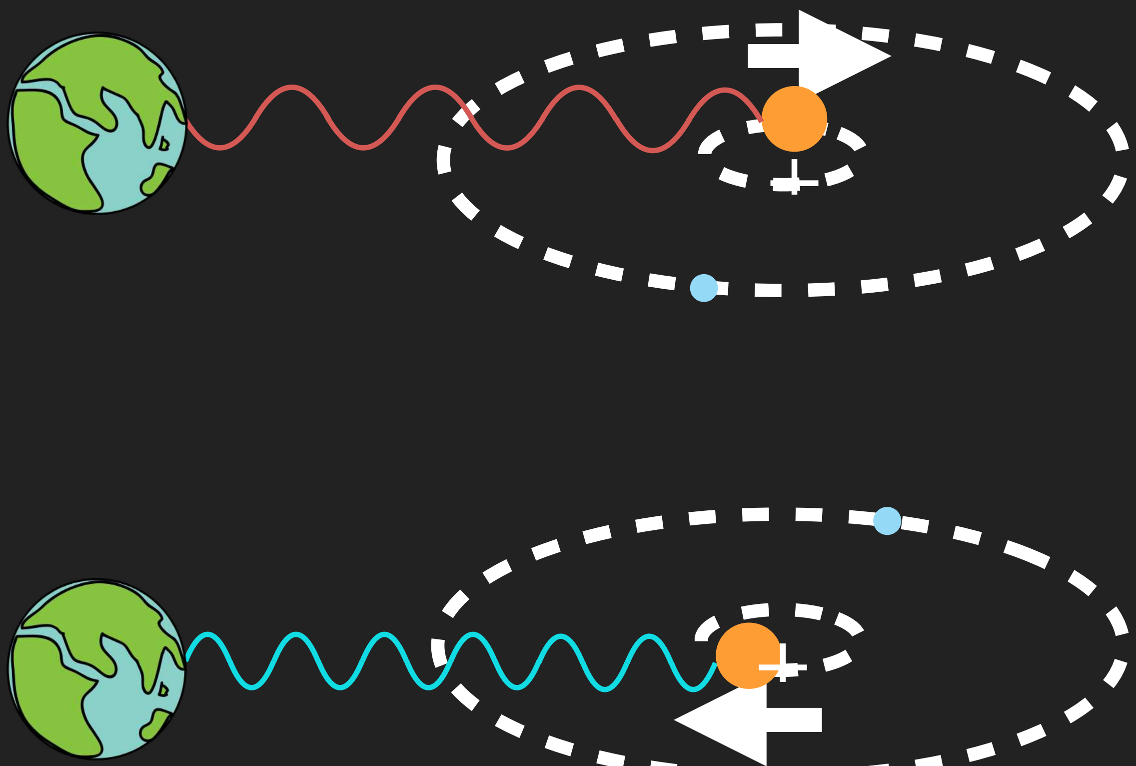
Give different planet properties.

Radial velocity
or
Doppler wobble

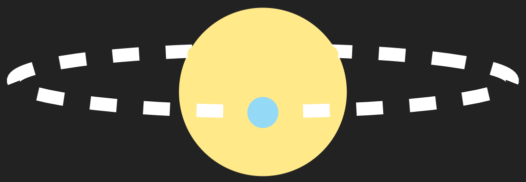


Star "wobbles" due to the planet's gravity.

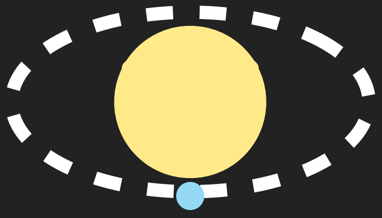
Periodic shift in wavelength



Gives a minimum mass for the planet

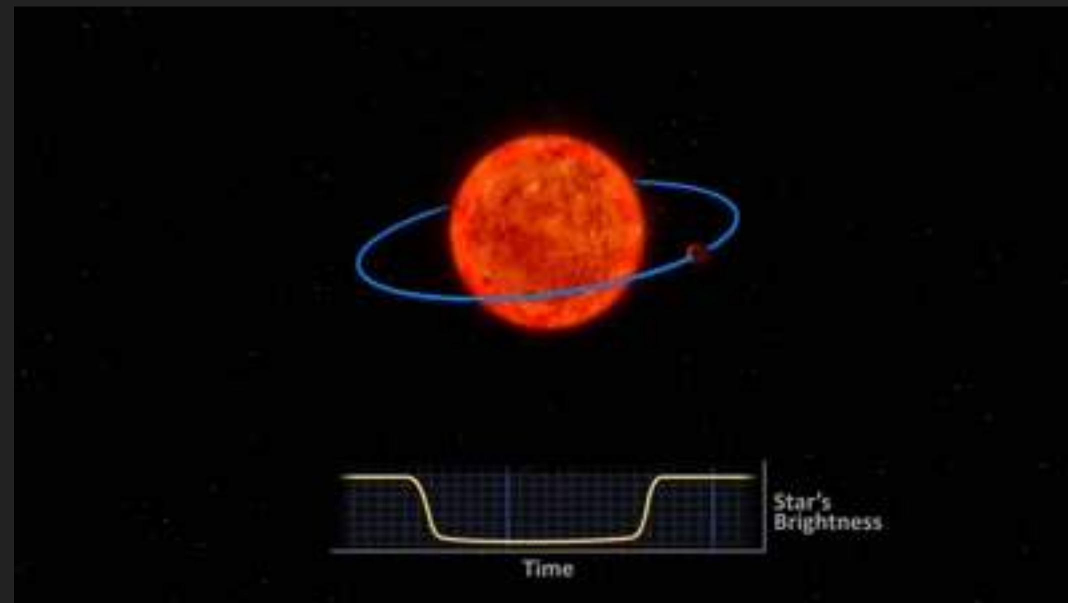


m sin (i) = mass

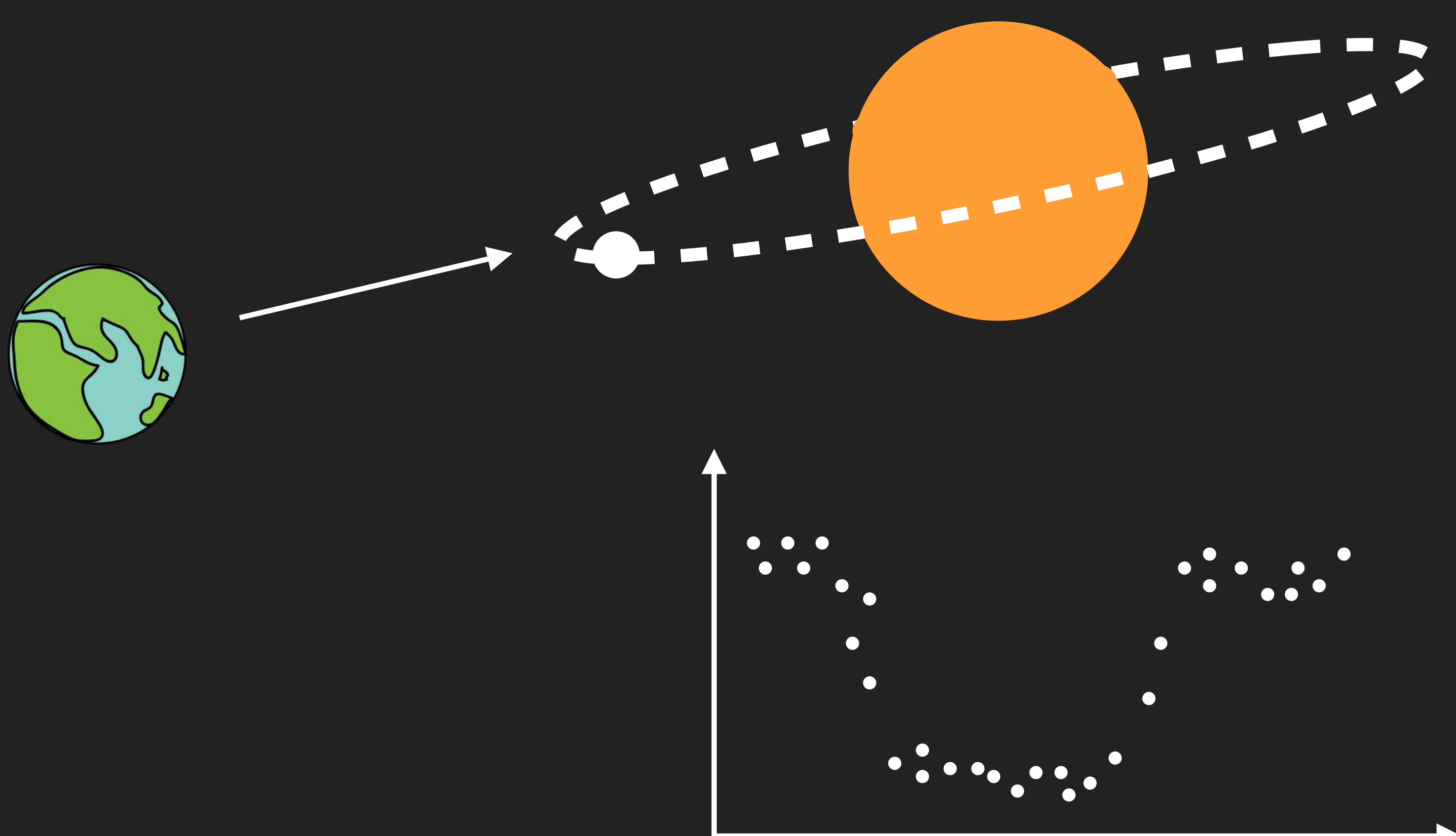


m sin (i) << mass

Transit

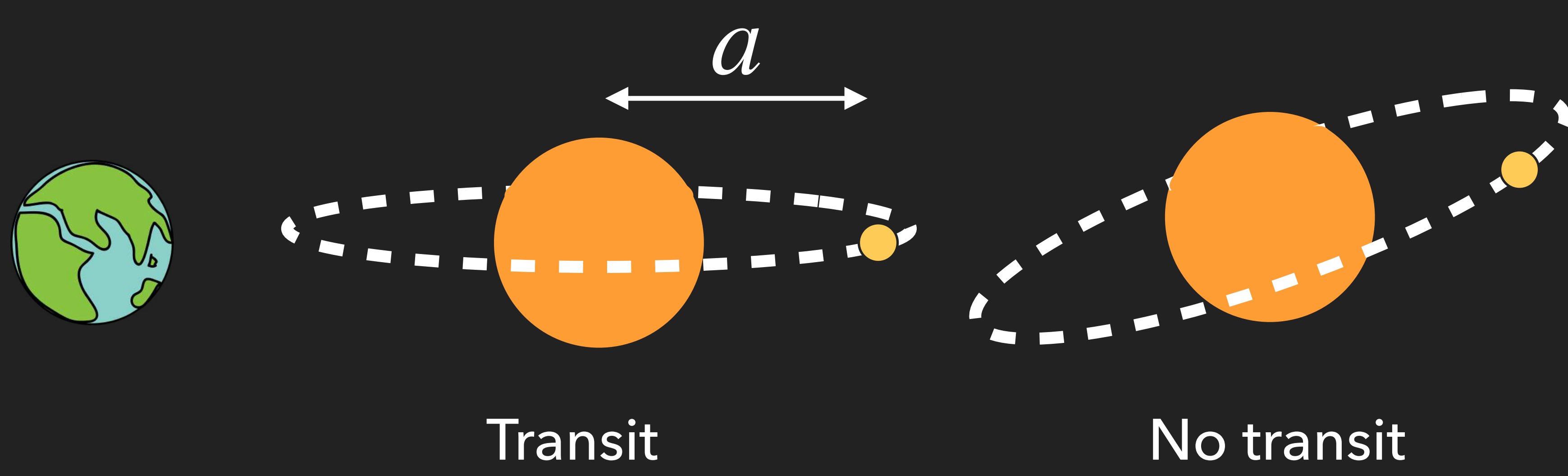


Dip in light as planet crosses our line of sight to the star



Gives a radius for the planet

Radius

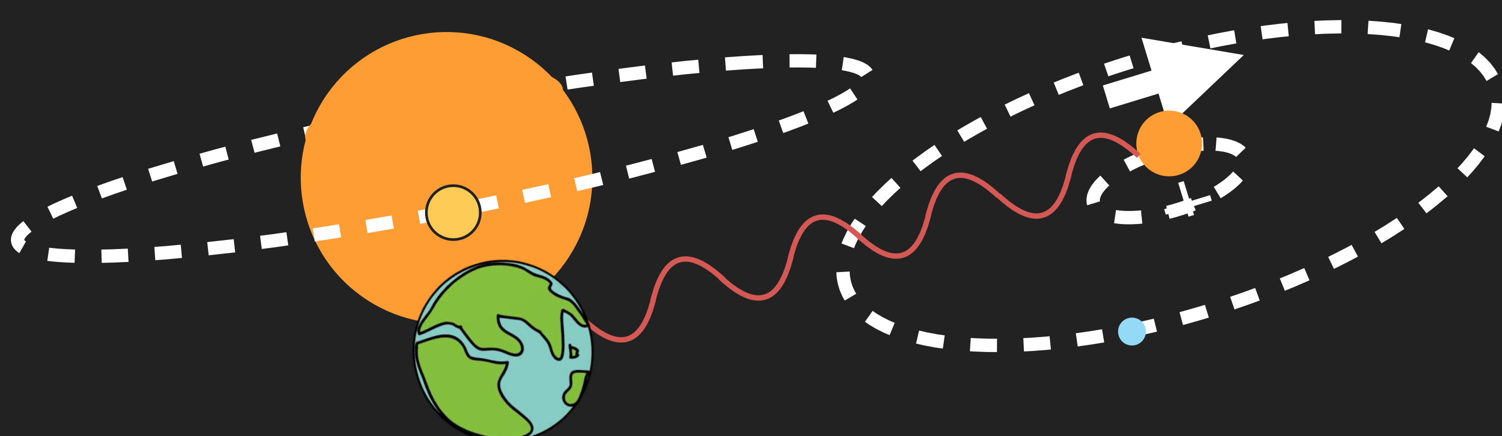


Transit required

$$p_T = \frac{R_*}{a}$$

Low probability far from star.

Mass



Detection by 2 methods required

(often impossible)

Planet characterisation needs mass & radius.

Gas

Hybrid

Rocky

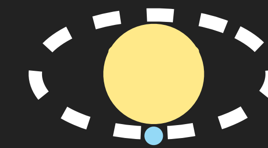
Ice

Proxima Centauri b

(Nearest star)

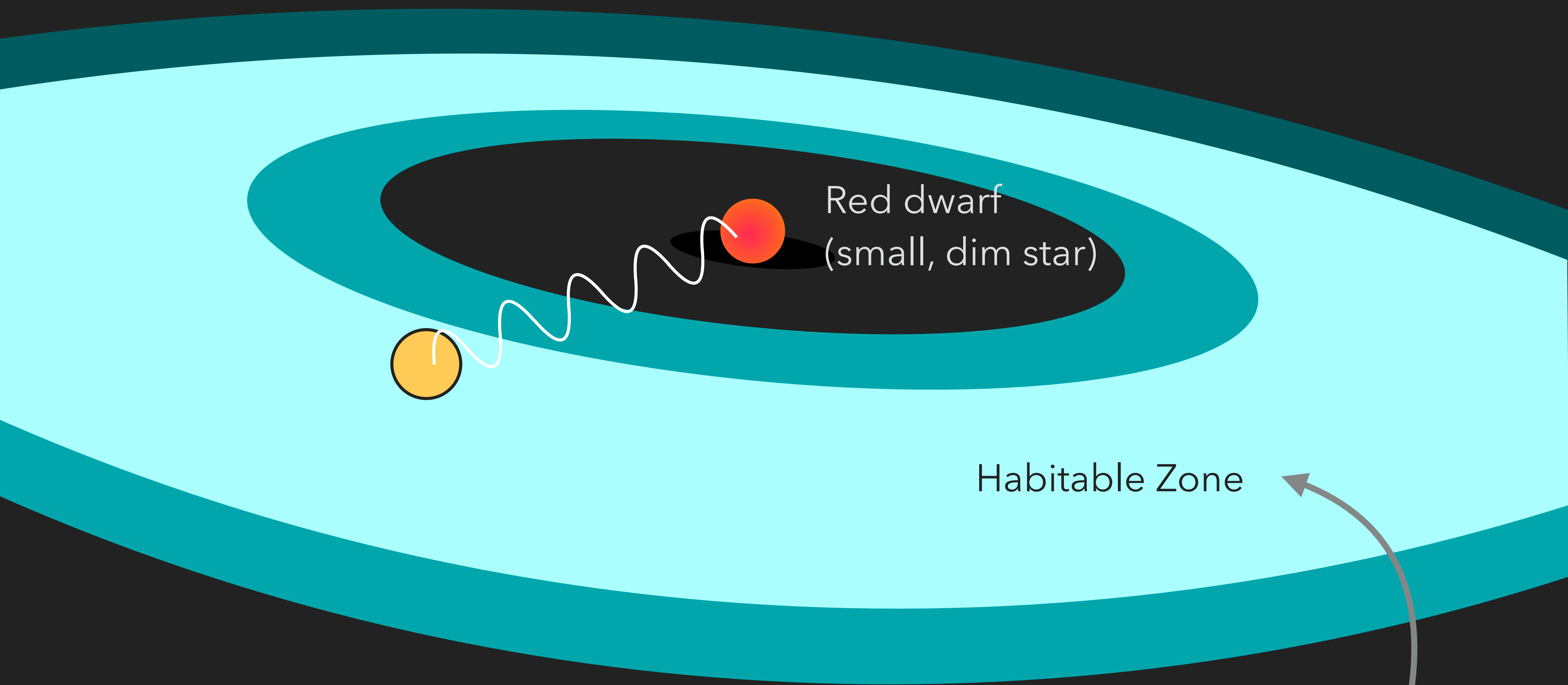
$M \sin(i) = 1.27\, \mathrm{M}_\oplus$

(min. mass)



(Radial velocity)

Period = 11.2 days



Earth could support liquid water

(assumes our surface pressure & atmosphere)

Proxima Centauri b

SURFACE IMAGING OF PROXIMA B AND OTHER EXOPLANETS: TOPOGRAPHY, BIOSIGNATURES, AND ARTIFICIAL MEGA-STRUCTURES

SEARCHING FOR THE TRANSIT OF THE EARTH-MASS EXOPLANET PROXIMA CENTAURI B IN ANTARCTICA: PRELIMINARY RESULT

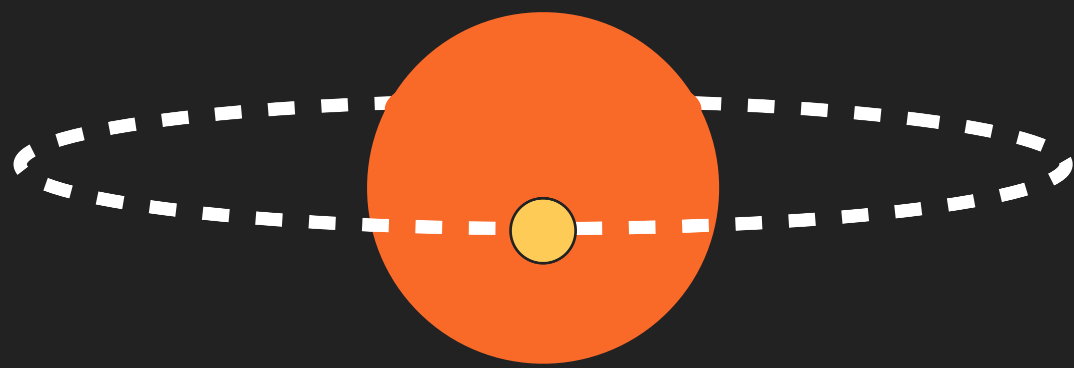
REDUCED DIVERSITY OF LIFE AROUND PROXIMA CENTAURI AND TRAPPIST-1

Exploring the climate of Proxima B with the Met Office Unified Model

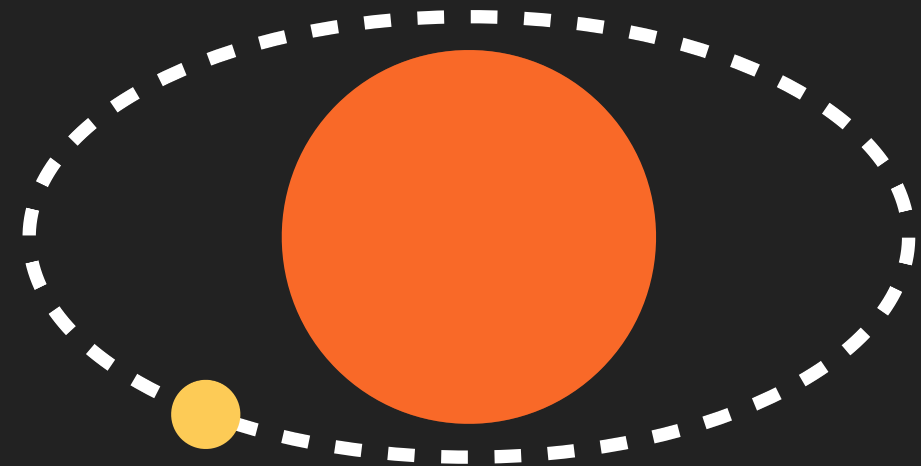
HABITABLE CLIMATE SCENARIOS FOR PROXIMA CENTAURI B WITH A DYNAMIC OCEAN

DETECTING PROXIMA B'S ATMOSPHERE WITH JWST TARGETING CO_2 AT 15 MICRON USING A HIGH-PASS SPECTRAL FILTERING TECHNIQUE

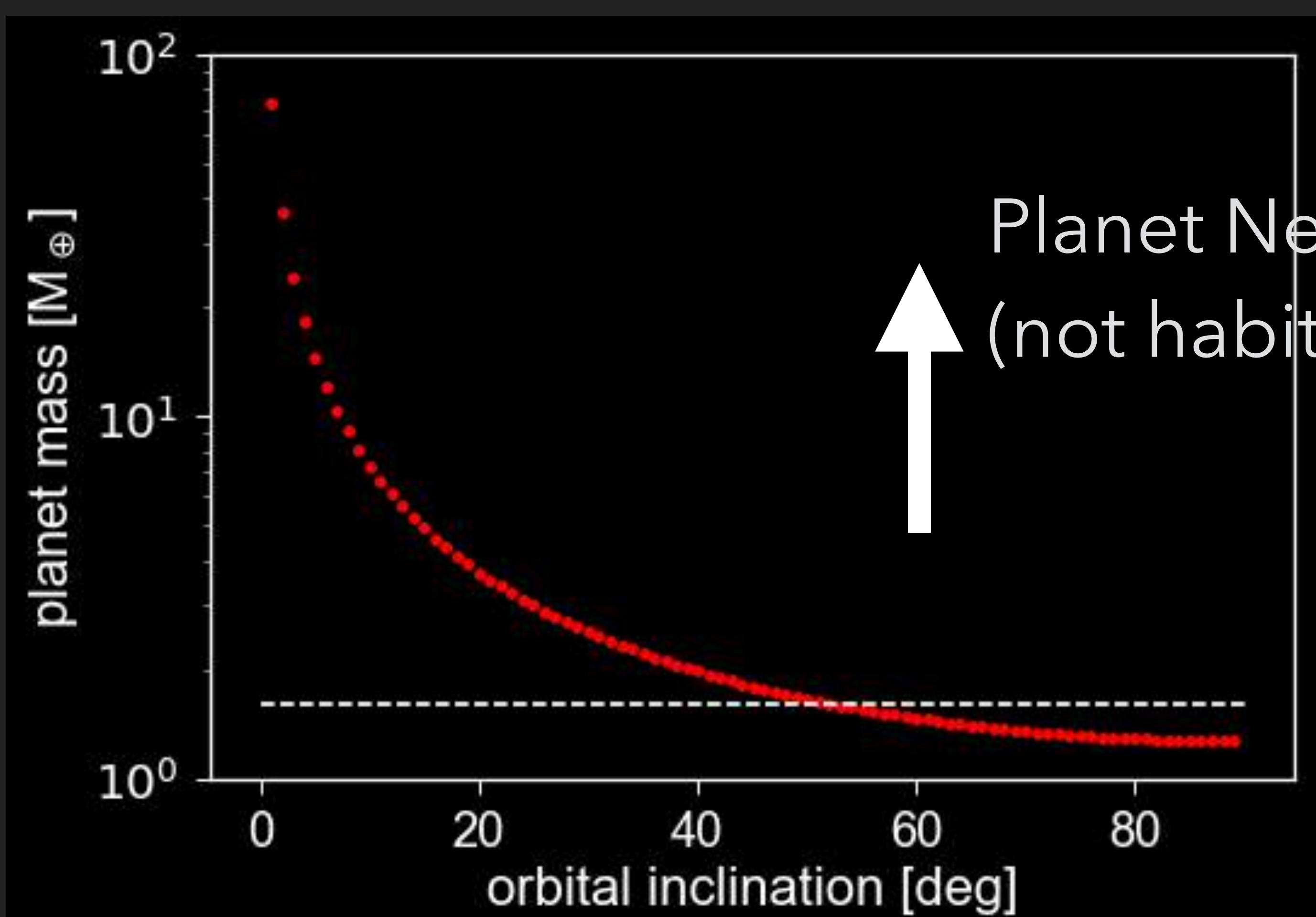
Proxima Centauri b : $M \sin(i) = 1.27\,\mathrm{M}_\oplus$



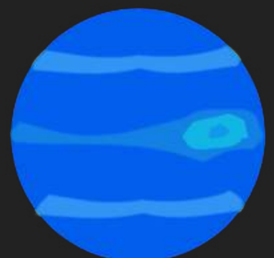
$M \sin(i = 90°) = M$



$M \sin(i < 90°) < M$



Planet Neptune-like
(not habitable!)



← empirical rocky planet limit

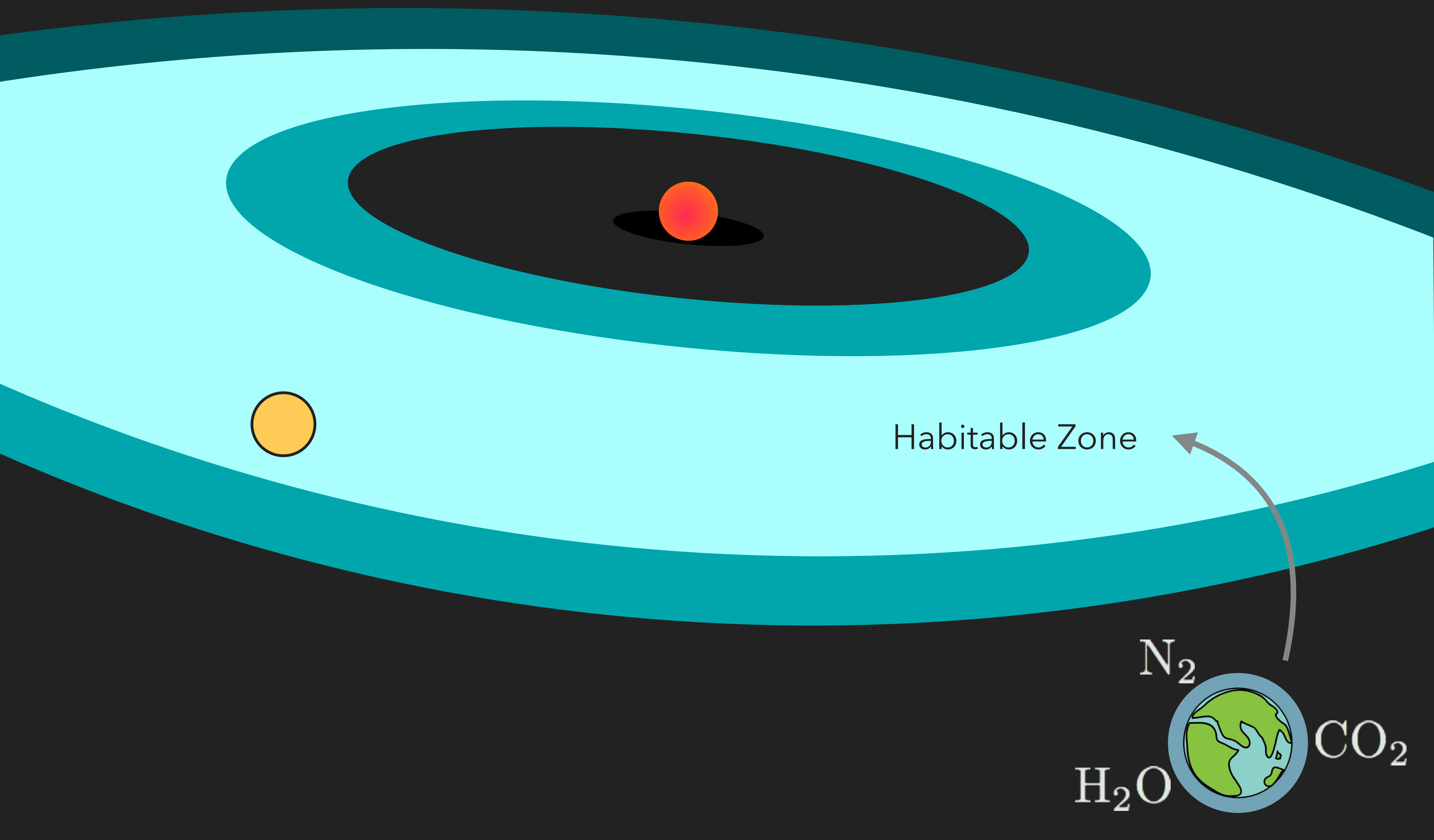
(Rogers, 2015, ApJ 801)

Kepler-186f

$R = 1.1 R_\oplus$

Period = 130 days

(Transit detection)

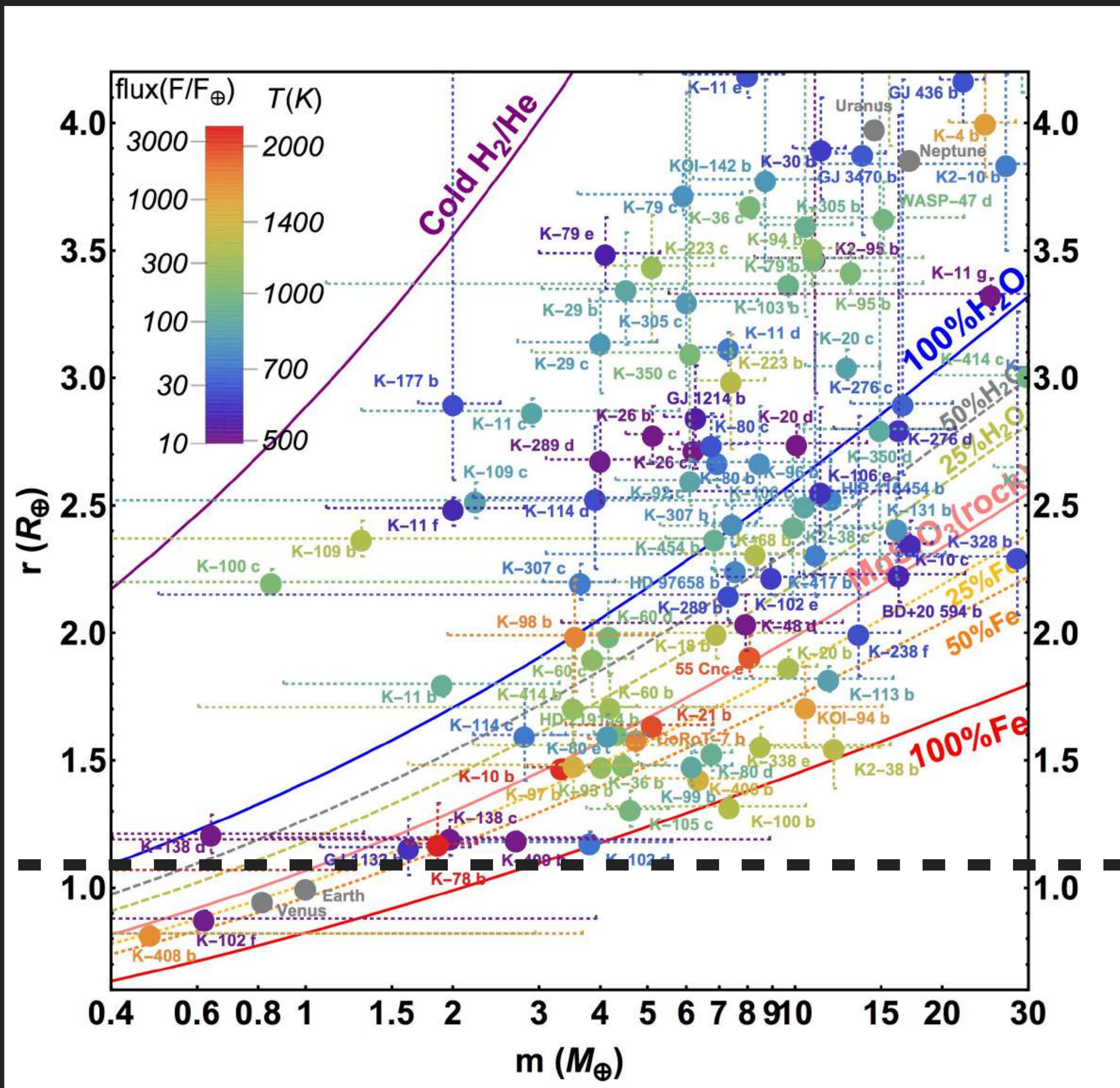


Kepler-186f

$$R = 1.1 R_\oplus$$

(Transit detection)

Period = 130 days

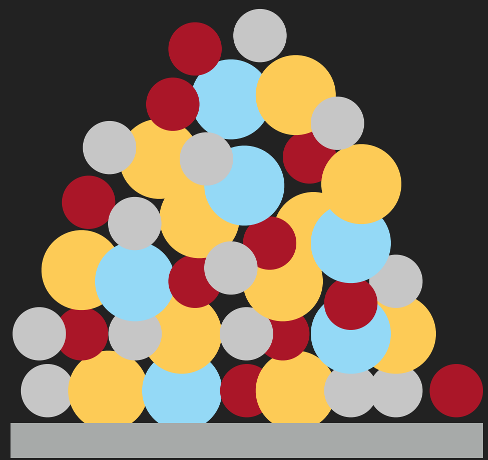


Degenerate compositions gives x10 spread in mass

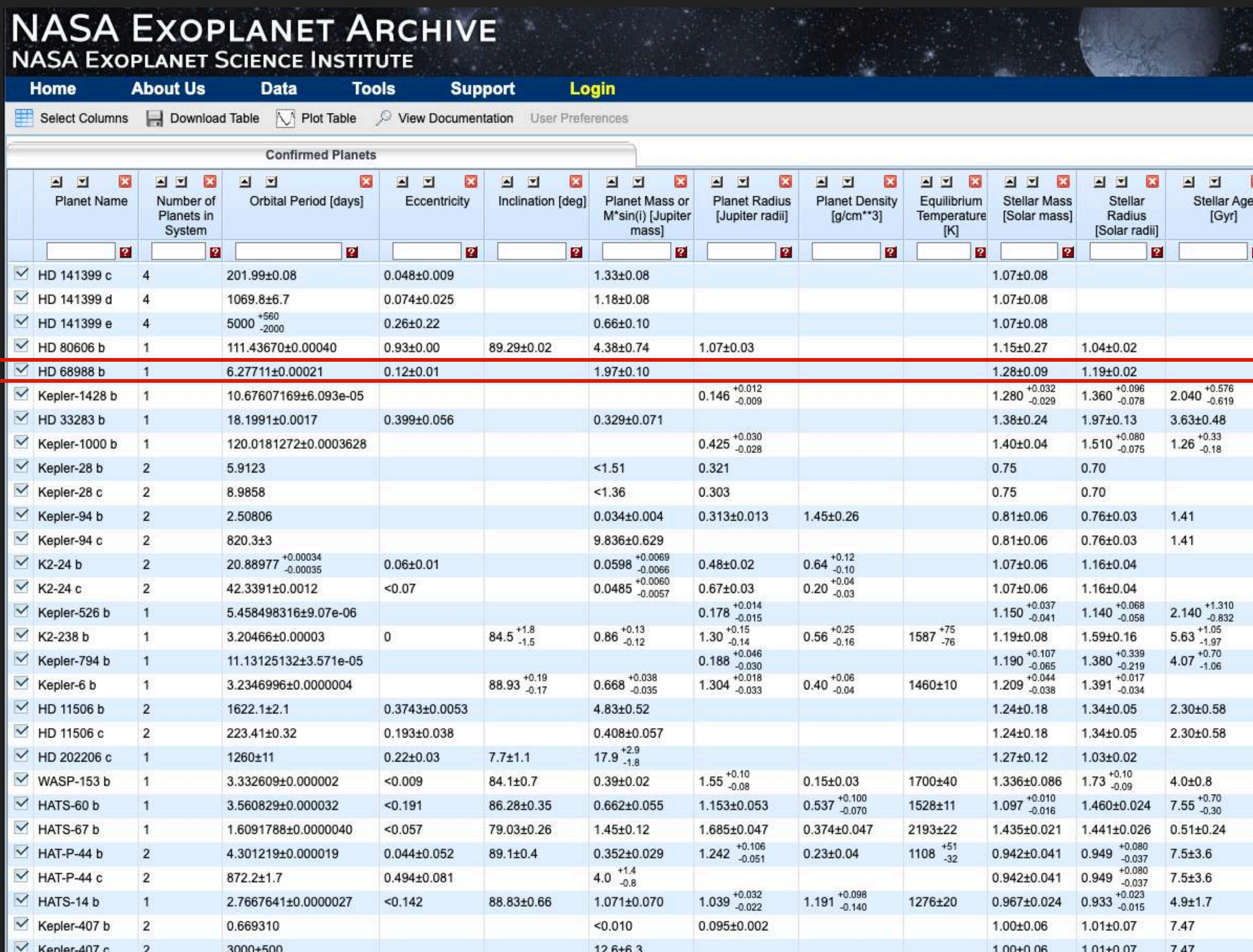
$$R = 1.1 R_\oplus$$

$$0.4 < M < 3.5\, M_\oplus$$

Lopez-Morales et al, ApJ 152:204, 2016



4000+ exoplanet discoveries



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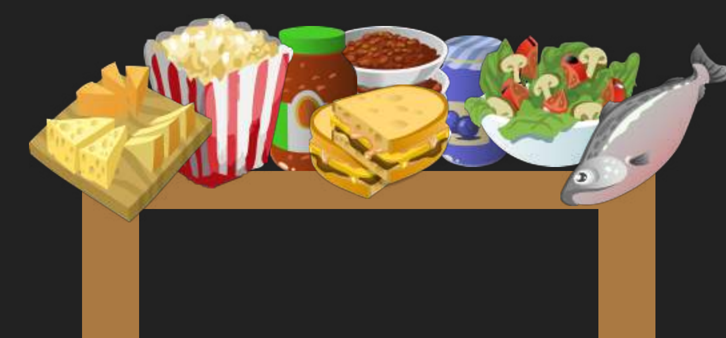
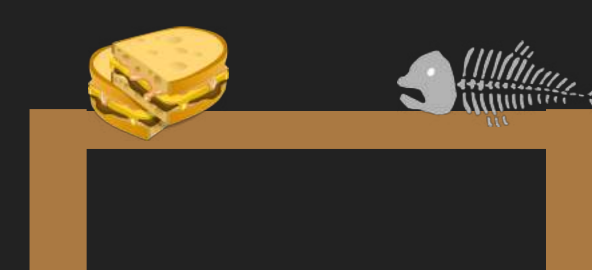
Confirmed Planets

Planet Name	Number of Planets in System	Orbital Period [days]	Eccentricity	Inclination [deg]	Planet Mass or M*sin(i) [Jupiter mass]	Planet Radius [Jupiter radii]	Planet Density [g/cm**3]	Equilibrium Temperature [K]	Stellar Mass [Solar mass]	Stellar Radius [Solar radii]	Stellar Age [Gyr]
HD 141399 c	4	201.99±0.08	0.048±0.009		1.33±0.08				1.07±0.08		
HD 141399 d	4	1069.8±6.7	0.074±0.025		1.18±0.08				1.07±0.08		
HD 141399 e	4	5000^{+560}_{-2000}	0.26±0.22		0.66±0.10				1.07±0.08		
HD 80606 b	1	111.43670±0.00040	0.93±0.00	89.29±0.02	4.38±0.74	1.07±0.03			1.15±0.27	1.04±0.02	
HD 68988 b	1	6.27711±0.00021	0.12±0.01		1.97±0.10				1.28±0.09	1.19±0.02	
Kepler-1428 b	1	10.67607169±6.093e-05				$0.146^{+0.012}_{-0.009}$			$1.280^{+0.032}_{-0.029}$	$1.360^{+0.096}_{-0.078}$	$2.040^{+0.576}_{-0.619}$
HD 33283 b	1	18.1991±0.0017	0.399±0.056		0.329±0.071				1.38±0.24	1.97±0.13	3.63±0.48
Kepler-1000 b	1	120.0181272±0.0003628				$0.425^{+0.030}_{-0.028}$			1.40±0.04	$1.510^{+0.080}_{-0.075}$	$1.26^{+0.33}_{-0.18}$
Kepler-28 b	2	5.9123			<1.51	0.321			0.75	0.70	
Kepler-28 c	2	8.9858			<1.36	0.303			0.75	0.70	
Kepler-94 b	2	2.50806			0.034±0.004	0.313±0.013	1.45±0.26		0.81±0.06	0.76±0.03	1.41
Kepler-94 c	2	820.3±3			9.836±0.629				0.81±0.06	0.76±0.03	1.41
K2-24 b	2	$20.88977^{+0.00034}_{-0.00035}$	0.06±0.01		$0.0598^{+0.0069}_{-0.0066}$	0.48±0.02	$0.64^{+0.12}_{-0.10}$		1.07±0.06	1.16±0.04	
K2-24 c	2	42.3391±0.0012	<0.07		$0.0485^{+0.0060}_{-0.0057}$	0.67±0.03	$0.20^{+0.04}_{-0.03}$		1.07±0.06	1.16±0.04	
Kepler-526 b	1	5.458498316±9.07e-06				$0.178^{+0.014}_{-0.015}$			$1.150^{+0.037}_{-0.041}$	$1.140^{+0.068}_{-0.058}$	$2.140^{+1.310}_{-0.832}$
K2-238 b	1	3.20466±0.00003	0	$84.5^{+1.8}_{-1.5}$	$0.86^{+0.13}_{-0.12}$	$1.30^{+0.15}_{-0.14}$	$0.56^{+0.25}_{-0.16}$	1587^{+75}_{-76}	1.19±0.08	1.59±0.16	$5.63^{+1.05}_{-1.97}$
Kepler-794 b	1	11.13125132±3.571e-05				$0.188^{+0.046}_{-0.030}$			$1.190^{+0.107}_{-0.065}$	$1.380^{+0.339}_{-0.219}$	$4.07^{+0.70}_{-1.06}$
Kepler-6 b	1	3.2346996±0.0000004		$88.93^{+0.19}_{-0.17}$	$0.668^{+0.038}_{-0.035}$	$1.304^{+0.018}_{-0.033}$	$0.40^{+0.06}_{-0.04}$	1460±10	$1.209^{+0.044}_{-0.038}$	$1.391^{+0.017}_{-0.034}$	
HD 11506 b	2	1622.1±2.1	0.3743±0.0053		4.83±0.52				1.24±0.18	1.34±0.05	2.30±0.58
HD 11506 c	2	223.41±0.32	0.193±0.038		0.408±0.057				1.24±0.18	1.34±0.05	2.30±0.58
HD 202206 c	1	1260±11	0.22±0.03	7.7±1.1	$17.9^{+2.9}_{-1.8}$				1.27±0.12	1.03±0.02	
WASP-153 b	1	3.332609±0.000002	<0.009	84.1±0.7	0.39±0.02	$1.55^{+0.10}_{-0.08}$	0.15±0.03	1700±40	1.336±0.086	$1.73^{+0.10}_{-0.09}$	4.0±0.8
HATS-60 b	1	3.560829±0.000032	<0.191	86.28±0.35	0.662±0.055	1.153±0.053	$0.537^{+0.100}_{-0.070}$	1528±11	$1.097^{+0.010}_{-0.016}$	1.460±0.024	$7.55^{+0.70}_{-0.30}$
HATS-67 b	1	1.6091788±0.0000040	<0.057	79.03±0.26	1.45±0.12	1.685±0.047	0.374±0.047	2193±22	1.435±0.021	1.441±0.026	0.51±0.24
HAT-P-44 b	2	4.301219±0.000019	0.044±0.052	89.1±0.4	0.352±0.029	$1.242^{+0.106}_{-0.051}$	0.23±0.04	1108^{+51}_{-32}	0.942±0.041	$0.949^{+0.080}_{-0.037}$	7.5±3.6
HAT-P-44 c	2	872.2±1.7	0.494±0.081		$4.0^{+1.4}_{-0.8}$				0.942±0.041	$0.949^{+0.080}_{-0.037}$	7.5±3.6
HATS-14 b	1	2.7667641±0.0000027	<0.142	88.83±0.66	1.071±0.070	$1.039^{+0.032}_{-0.022}$	$1.191^{+0.098}_{-0.140}$	1276±20	0.967±0.024	$0.933^{+0.023}_{-0.015}$	4.9±1.7
Kepler-407 b	2	0.669310			<0.010	0.095±0.002			1.00±0.06	1.01±0.07	7.47
Kepler-407 c	2	3000±500			12.6±6.3				1.00±0.06	1.01±0.07	7.47

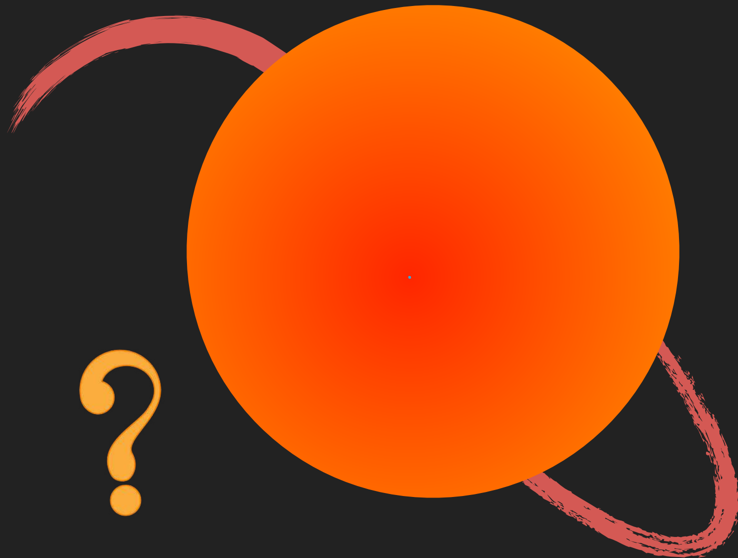
Many potential planet properties

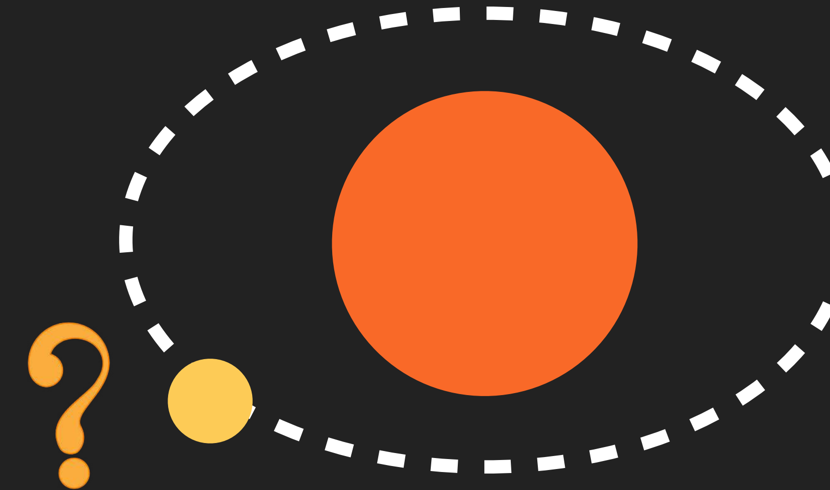


… sparse table



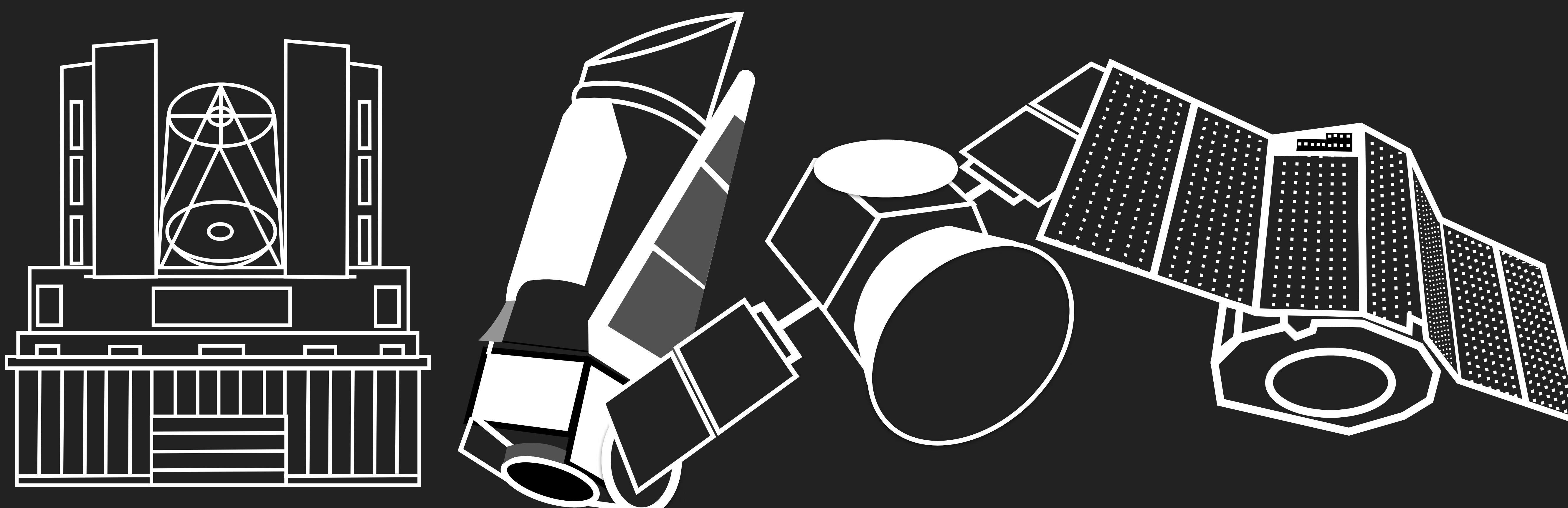
https://exoplanetarchive.ipac.caltech.edu

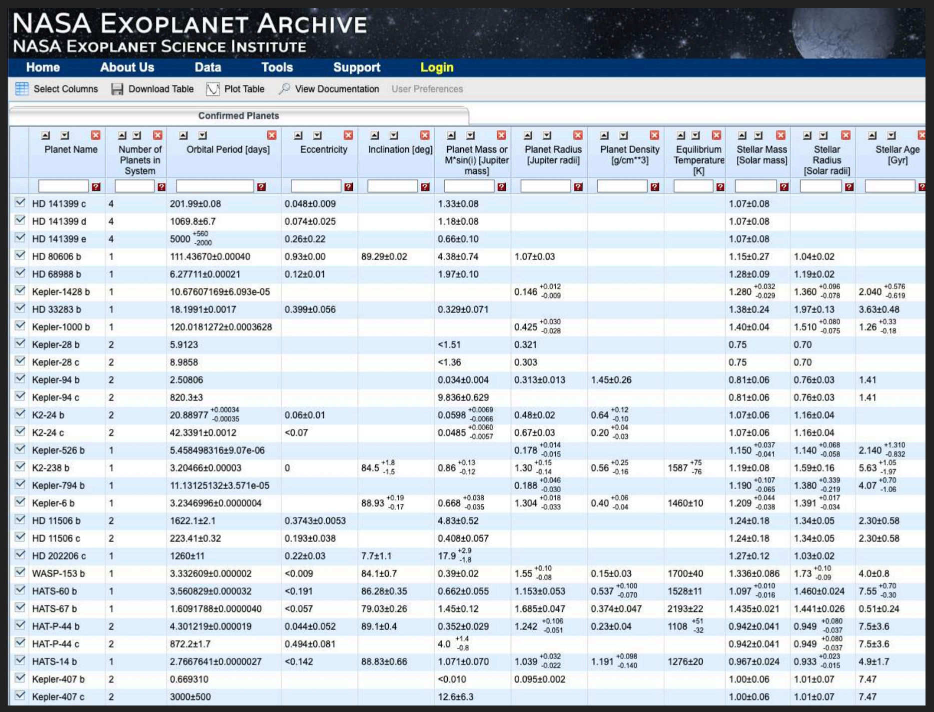




When telescopes cannot help…

What can we do?





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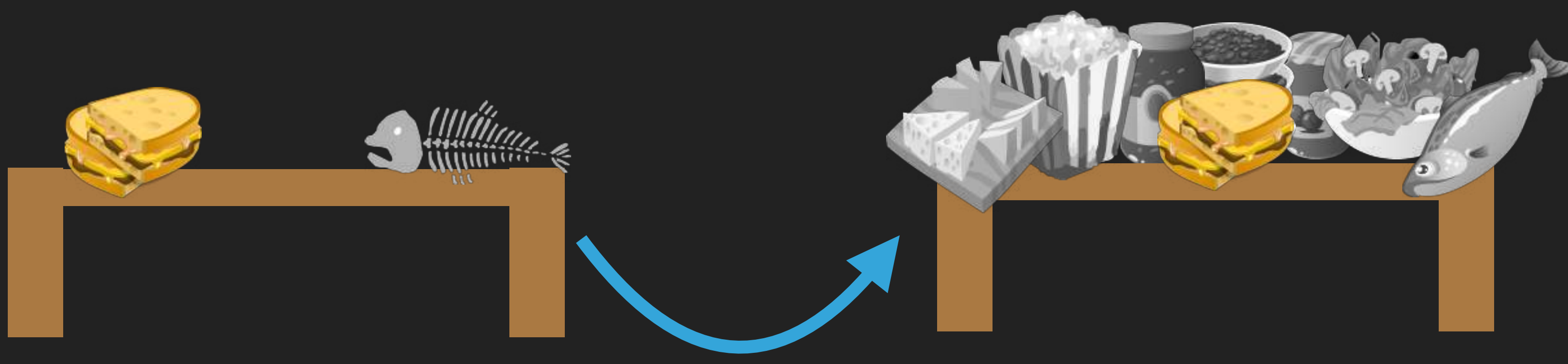
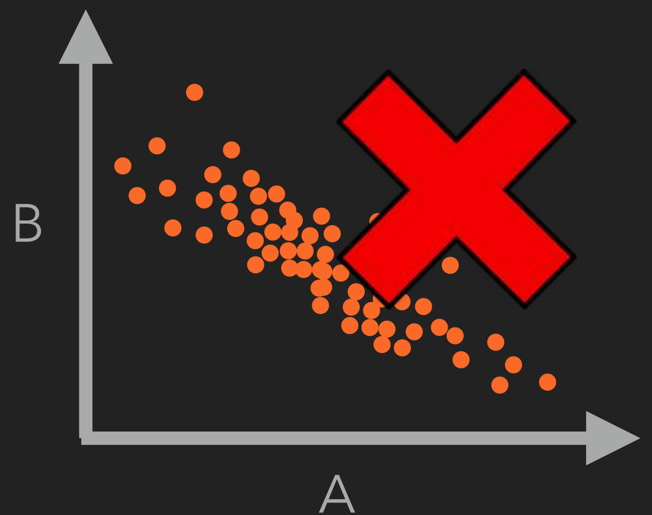
HAT-P-44 b	2	4.301219±0.000019	0.044±0.052	89.1±0.4	0.352±0.029	$1.242^{+0.106}_{-0.051}$	0.23±0.04	1108^{+51}_{-32}	0.942±0.041	$0.949^{+0.080}_{-0.037}$	7.5±3.6
HAT-P-44 c	2	872.2±1.7	0.494±0.081		$4.0^{+1.4}_{-0.8}$				0.942±0.041	$0.949^{+0.080}_{-0.037}$	7.5±3.6
HATS-14 b	1	2.7667641±0.0000027	<0.142	88.83±0.66	1.071±0.070	$1.039^{+0.032}_{-0.022}$	$1.191^{+0.098}_{-0.140}$	1276±20	0.967±0.024	$0.933^{+0.023}_{-0.015}$	4.9±1.7
Kepler-407 b	2	0.669310			<0.010	0.095±0.002			1.00±0.06	1.01±0.07	7.47
Kepler-407 c	2	3000±500			12.6±6.3				1.00±0.06	1.01±0.07	7.47

Can we impute missing values, based on known properties?

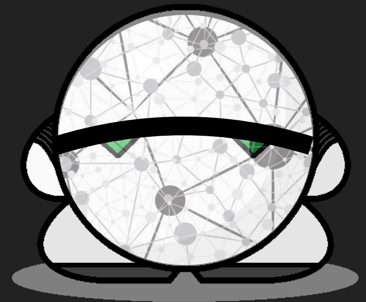


But...

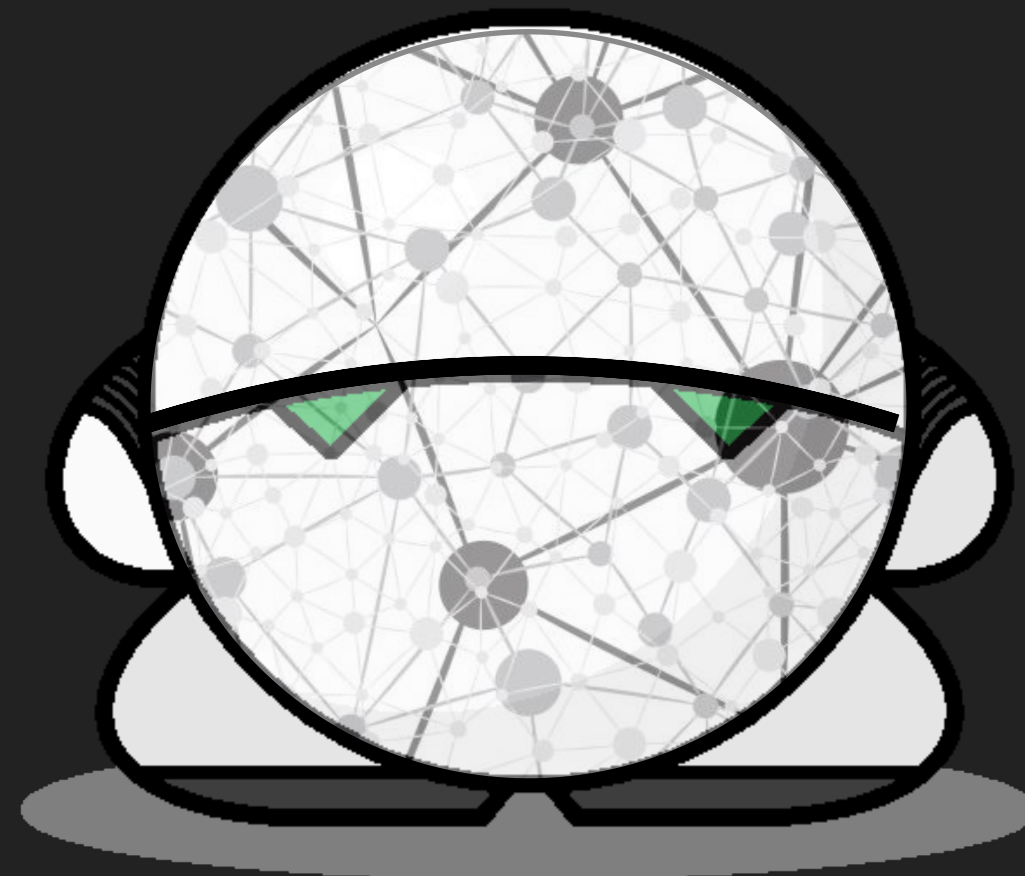


Multi-dimensional data

Incomplete planet formation theories



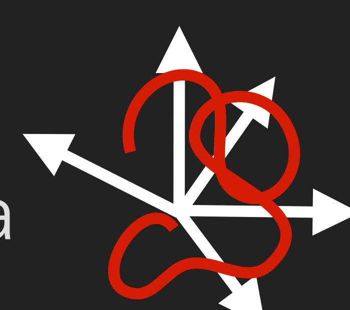
neural network: planet property generator



NEURAL NETWORK

Type of machine learning, inspired by the brain. 

Given examples, a neural network finds trends between variables.

Excellent for multi-dimensional data 

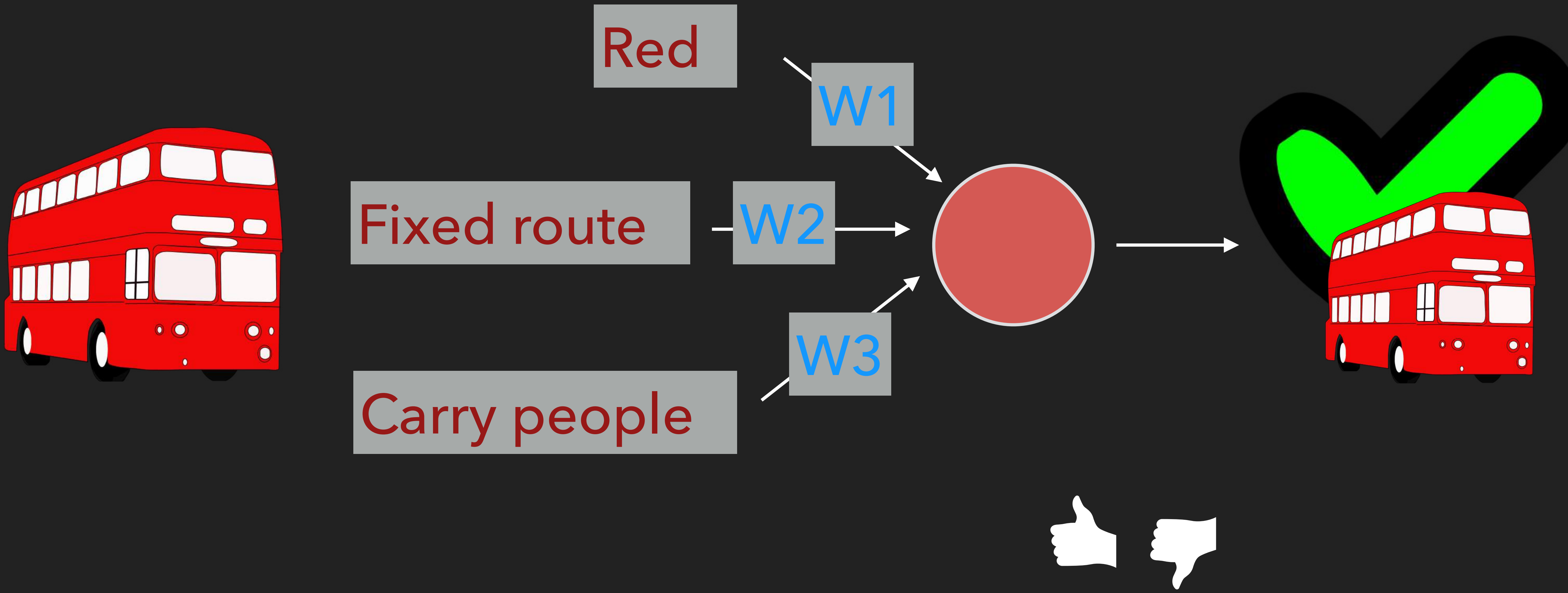

15
LONDON
15

15
LONDON
15
Red
Four wheels
Two floors
London
Carry people

Carry many people

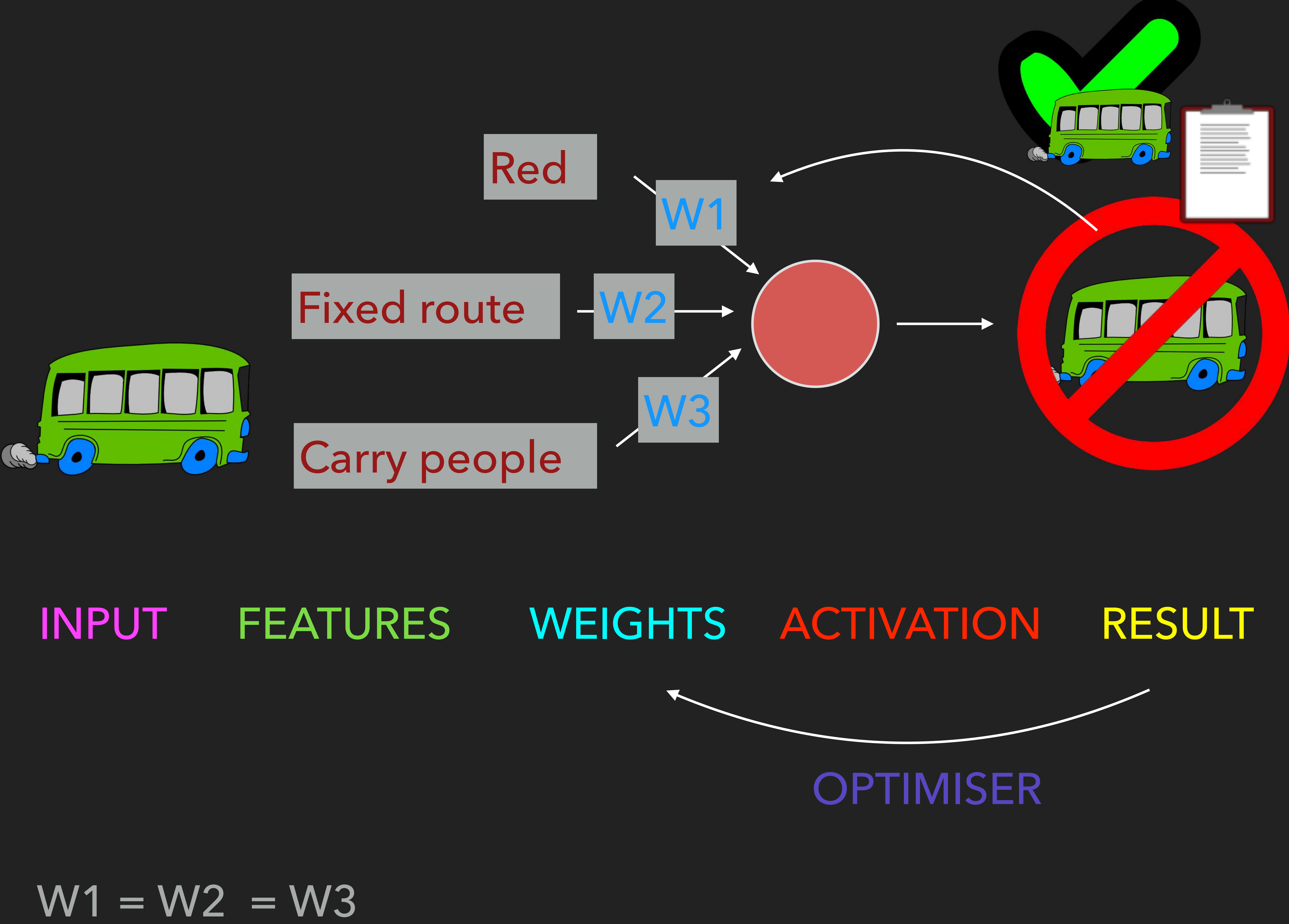
Fixed route

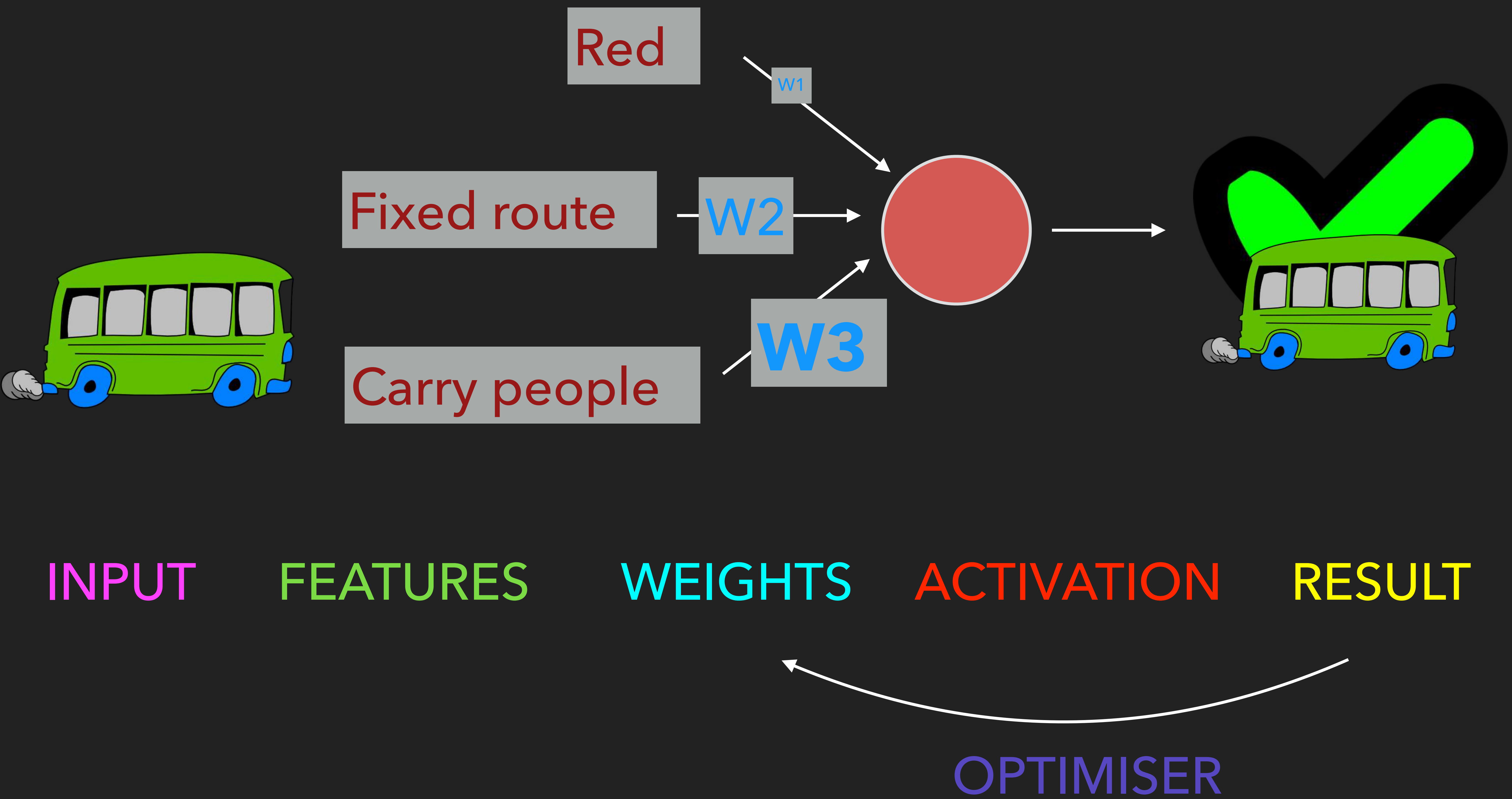
Involves a fee



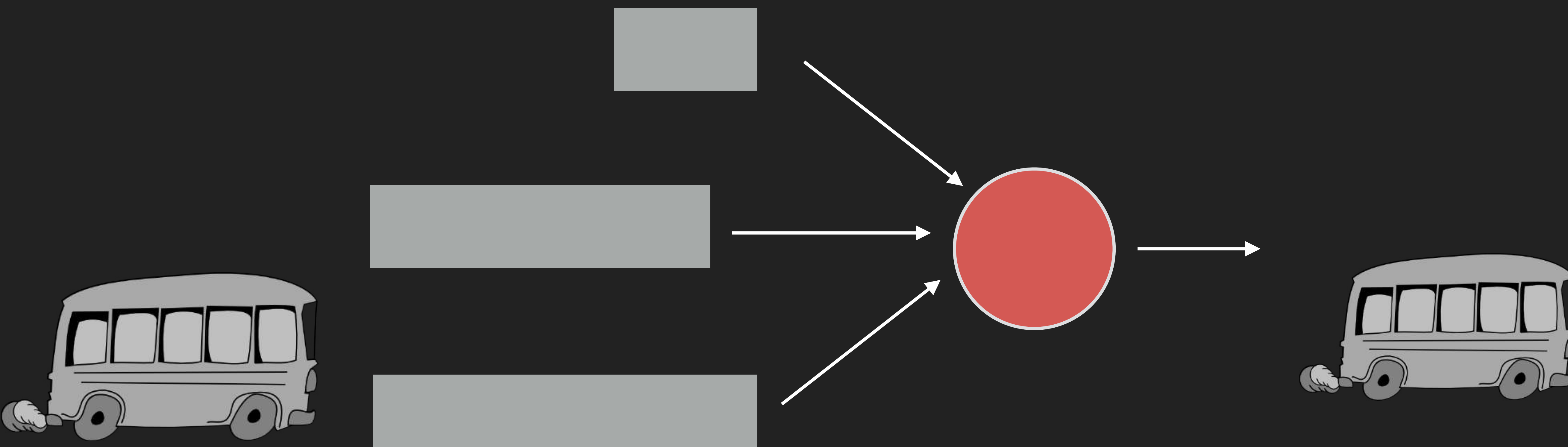
INPUT FEATURES WEIGHTS ACTIVATION RESULT

W1 = W2 = W3

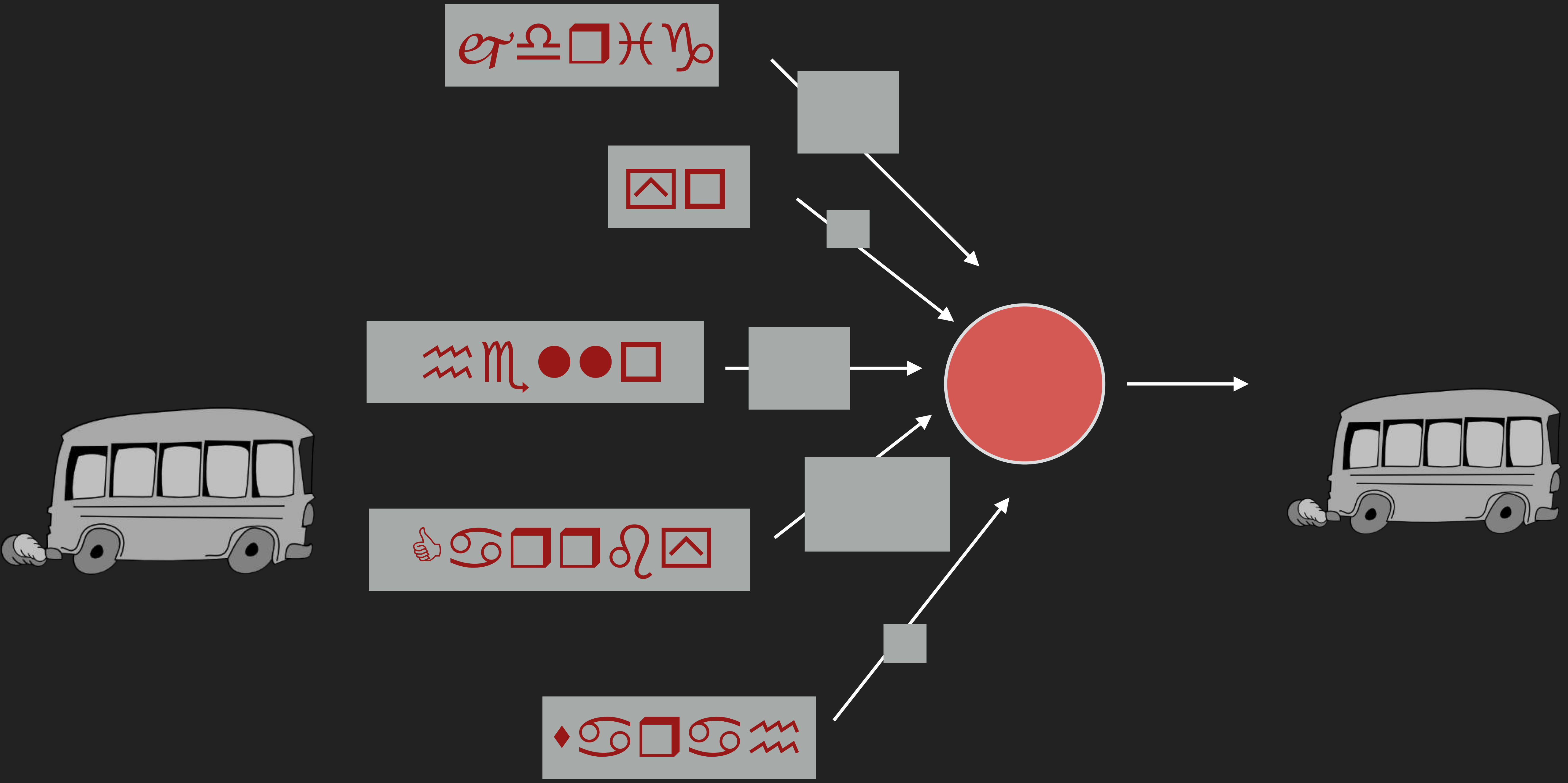

Red
W1
Fixed route
W2
W3
Carry people
INPUT
FEATURES
WEIGHTS
ACTIVATION
RESULT
OPTIMISER
W1 = W2 = W3


Red
W1
Fixed route
W2
Carry people
W3
INPUT
FEATURES
WEIGHTS
ACTIVATION
RESULT
OPTIMISER

W1 < W2 < W3

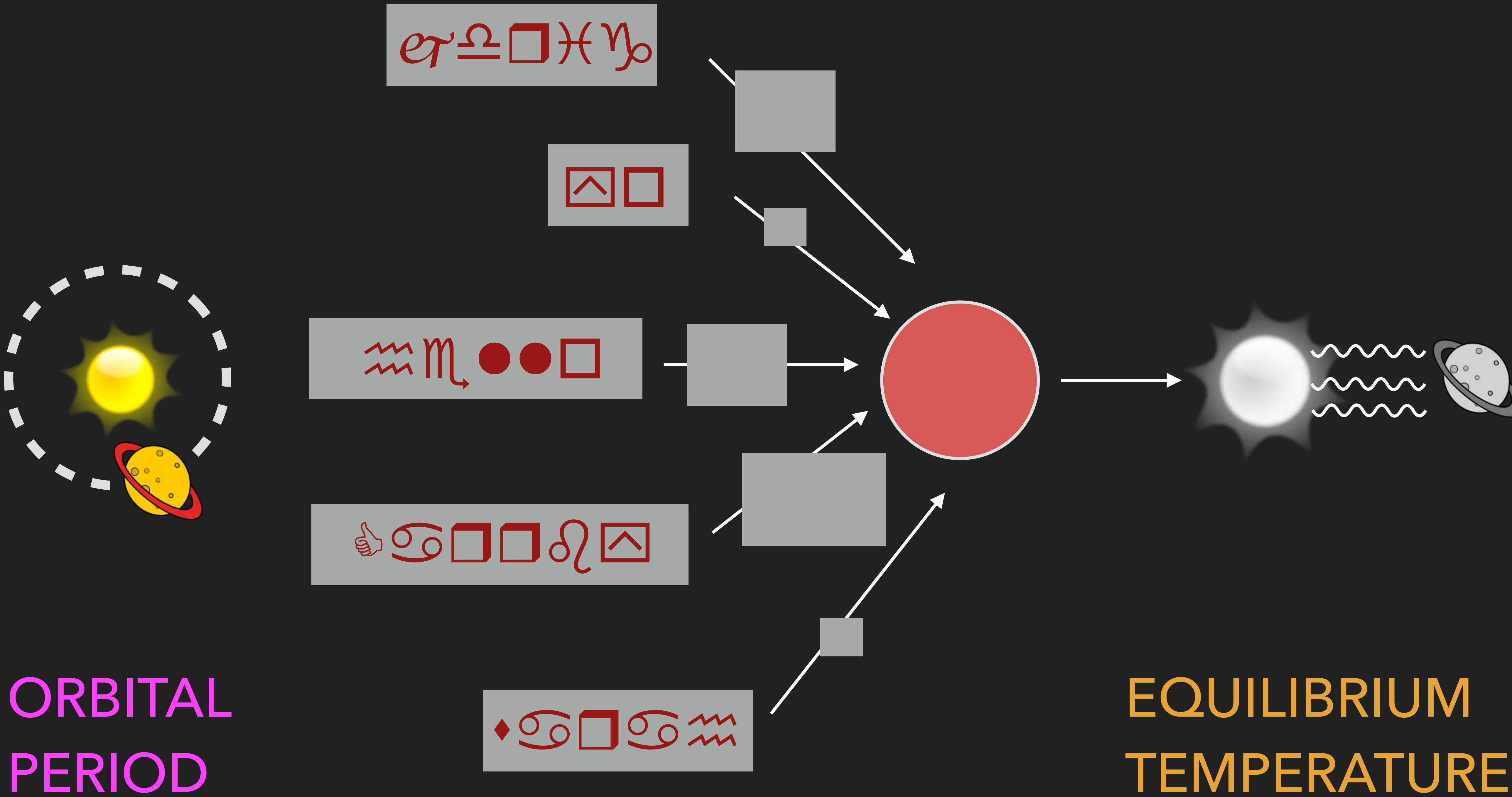


You can choose the number of features (nodes)



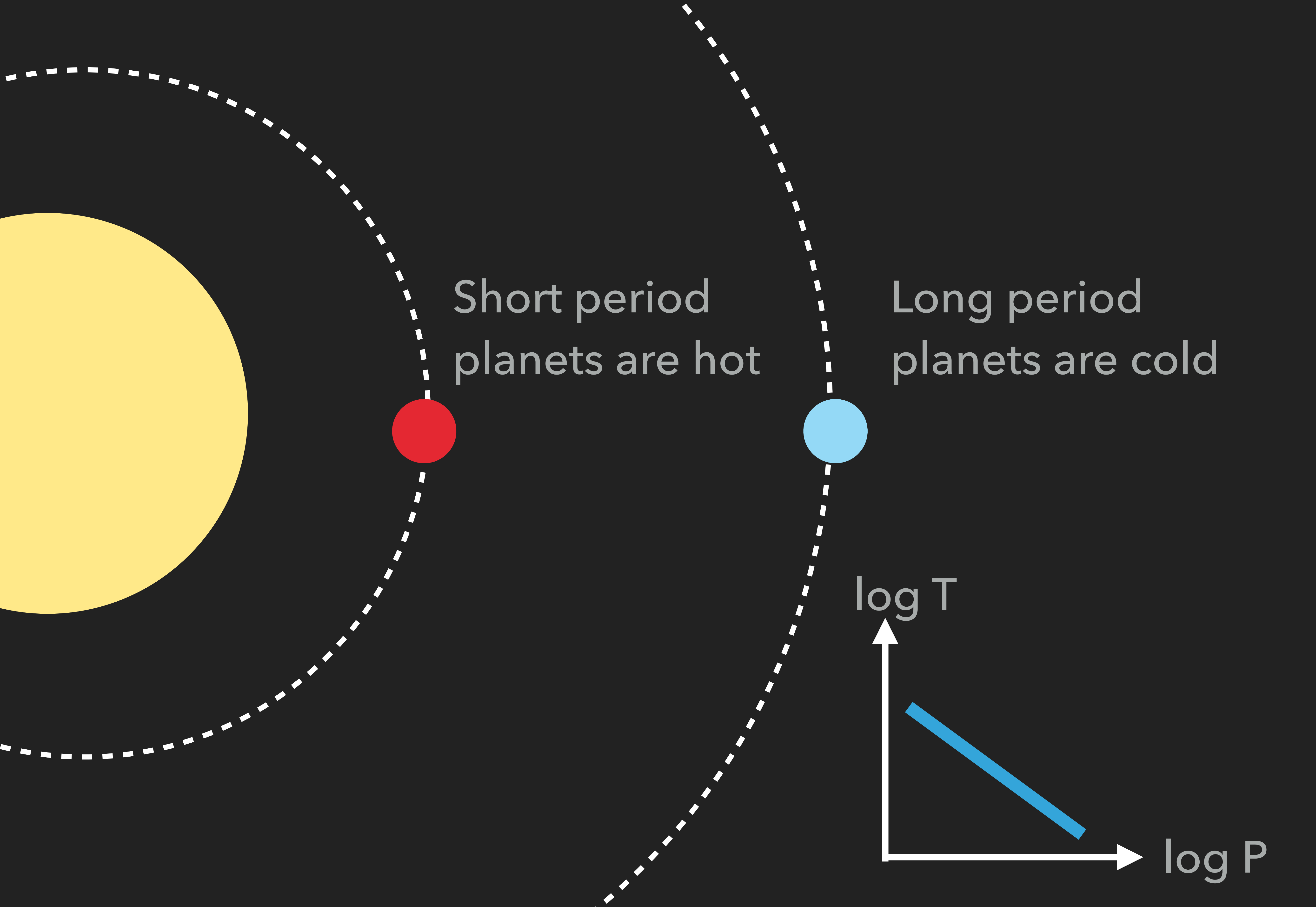
You can choose the number of features (nodes)

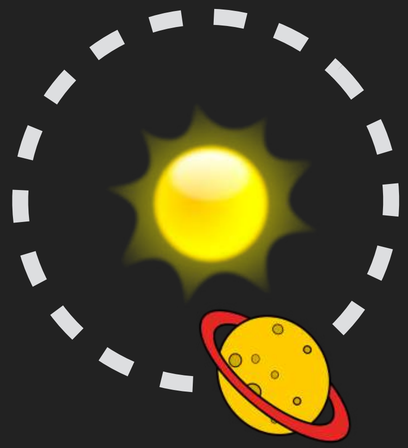
But the network selects what each node represents and its weight



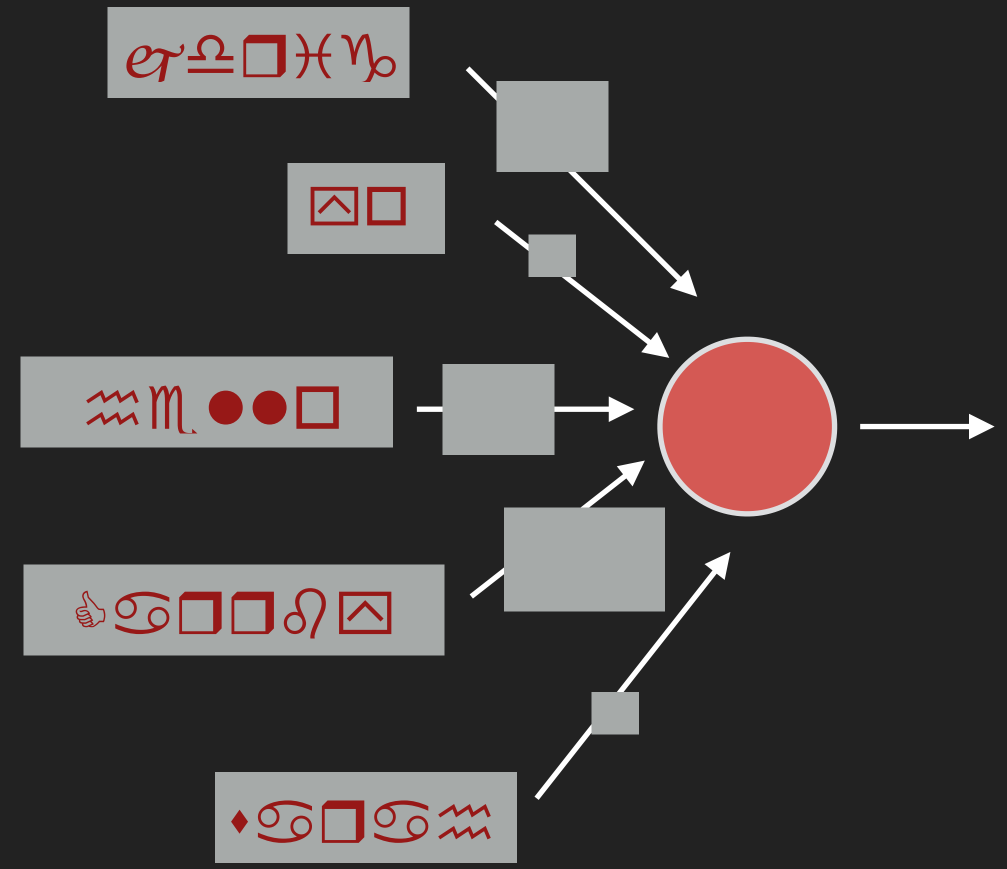
Can a neural network find the relation between orbital period and equilibrium temperature?

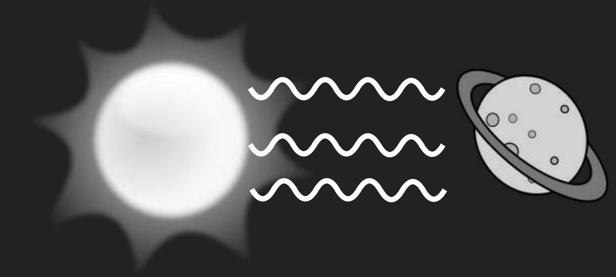
Not very difficult…



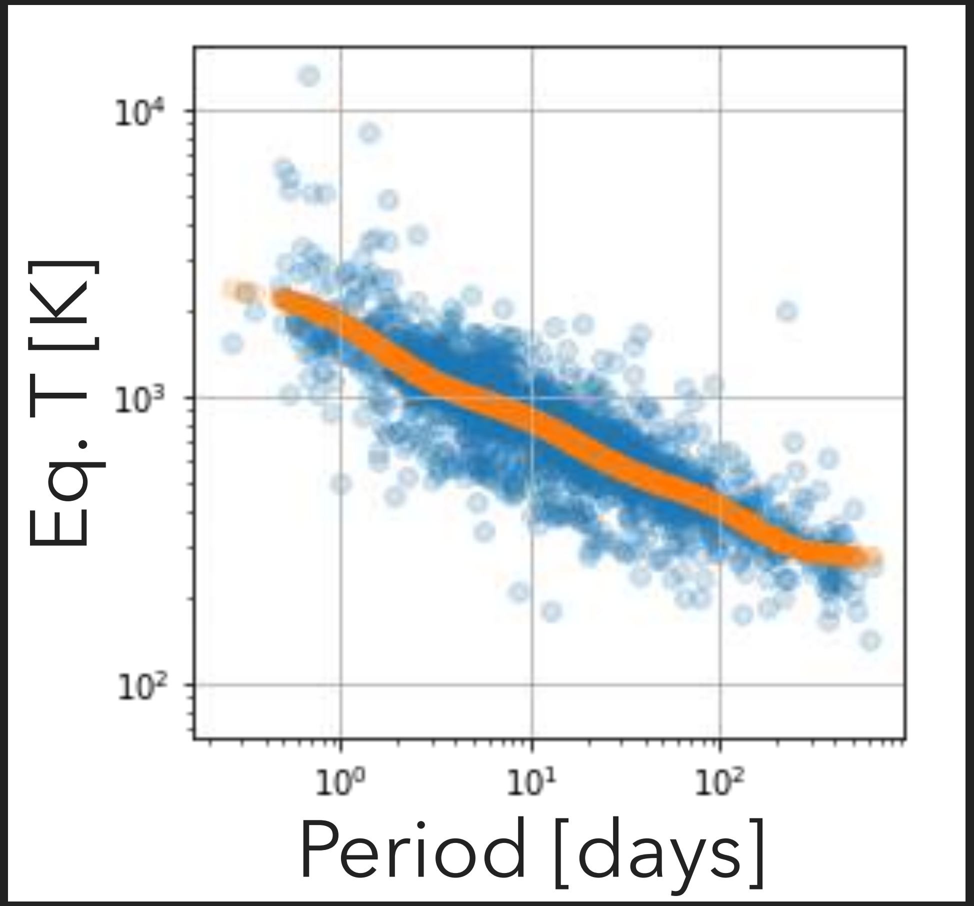


PERIOD





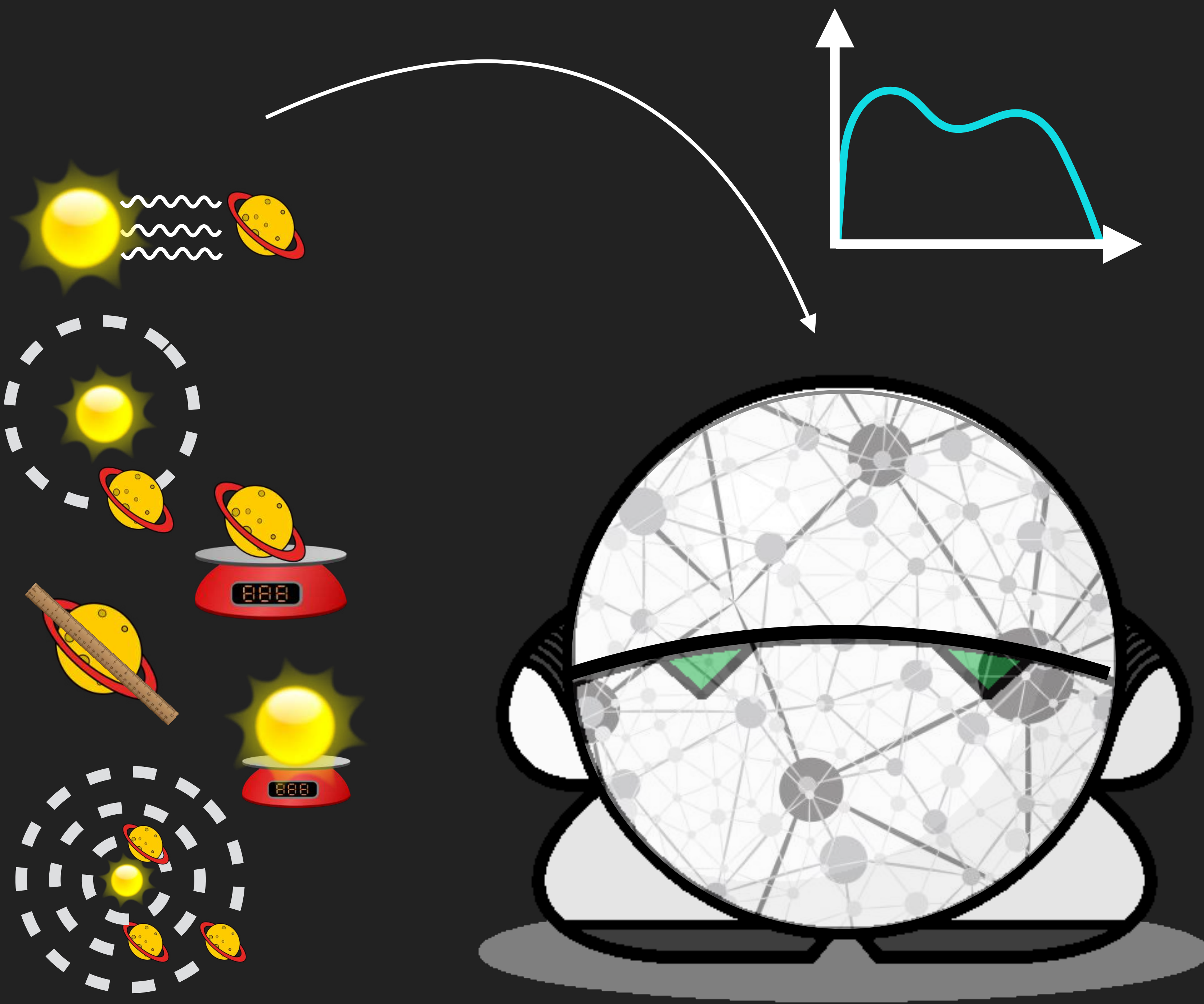
EQ. TEMP.



blue = data

orange = network prediction

But how do we train the network if we don't know the right answer?

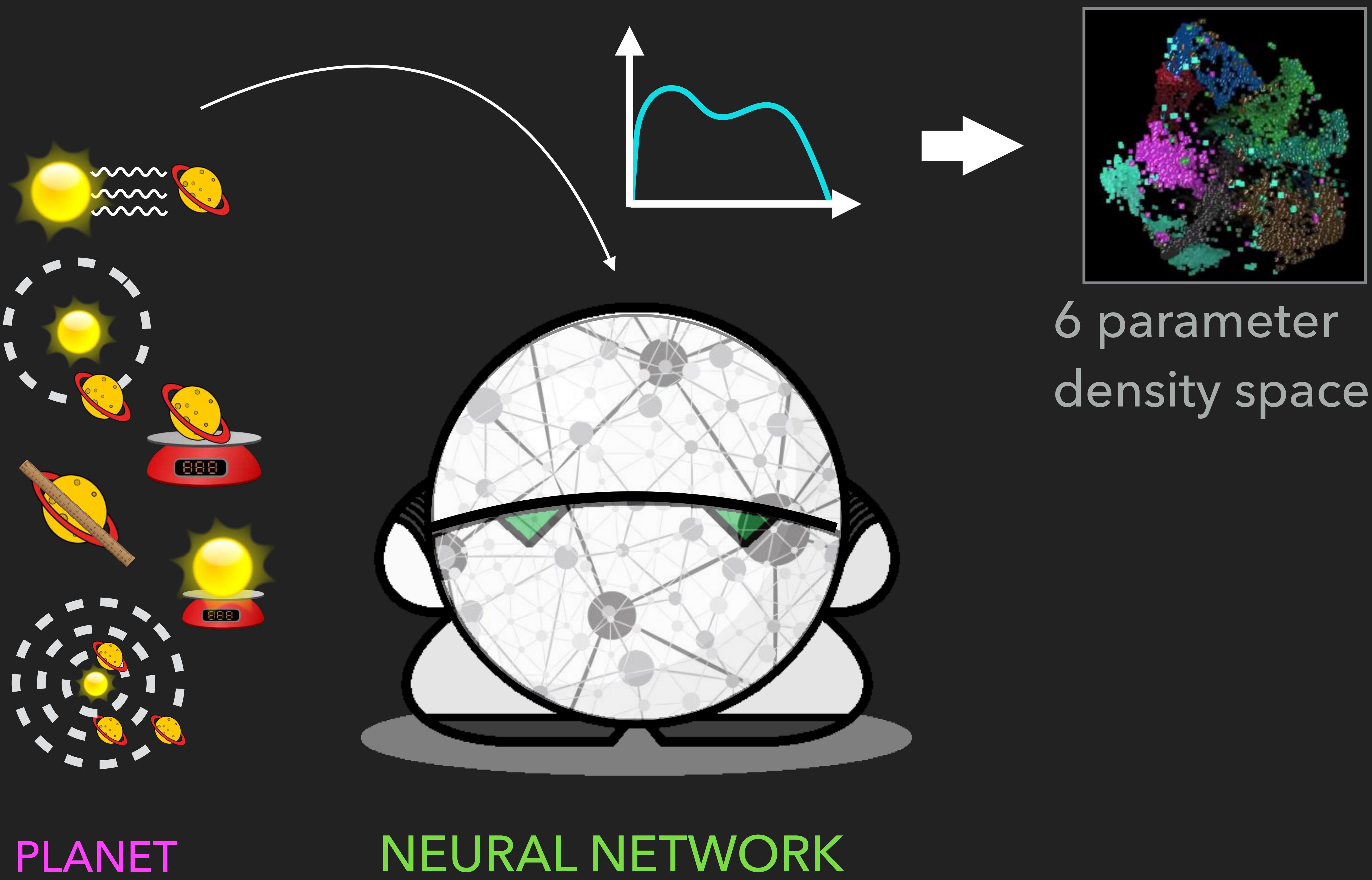


Feed the network a set of properties for many planets

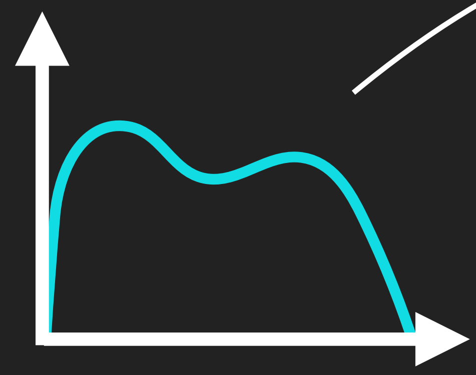
Network finds a statistical representation of those properties

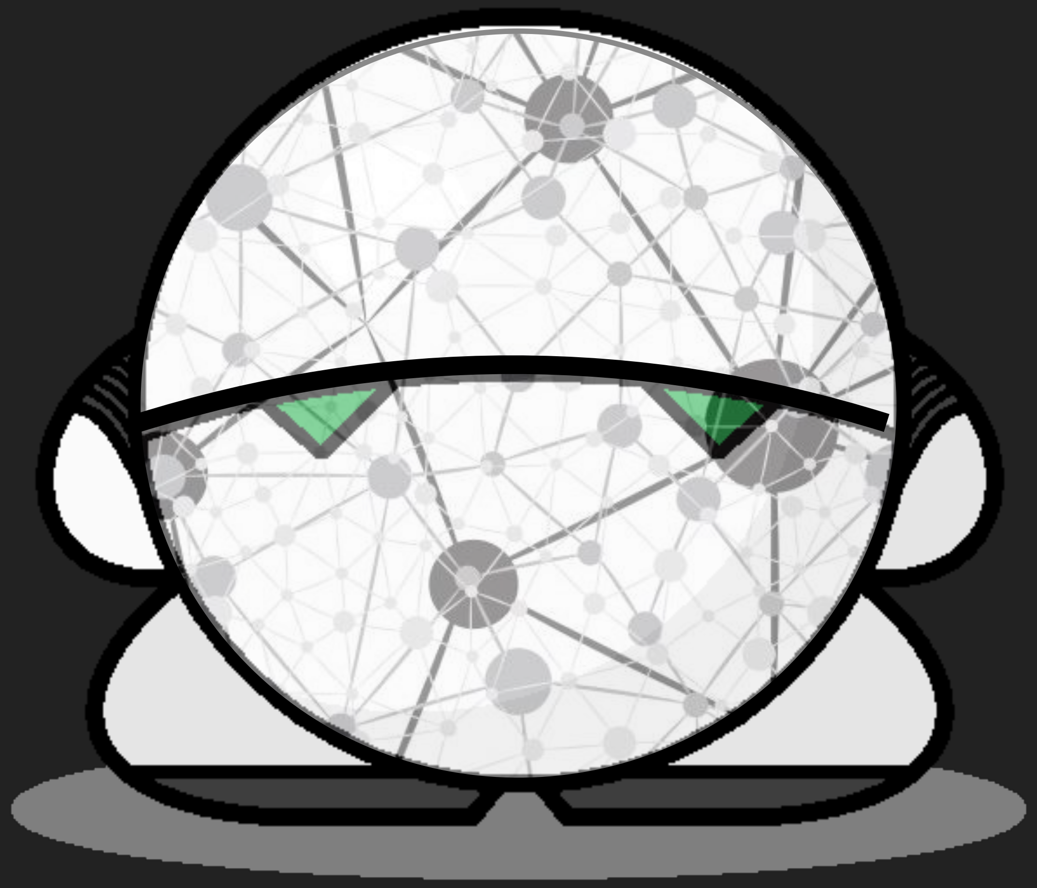
PLANET

NEURAL NETWORK

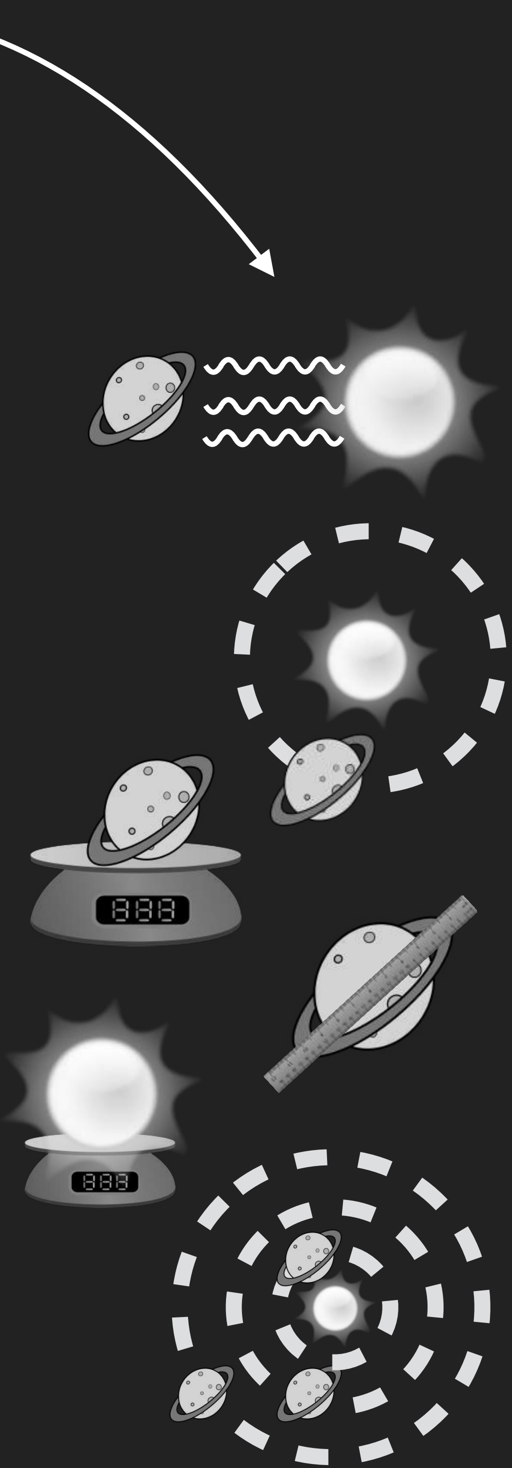

6 parameter
density space
PLANET
NEURAL NETWORK

Network can create a "new" planets whose properties fit the statistical distribution.



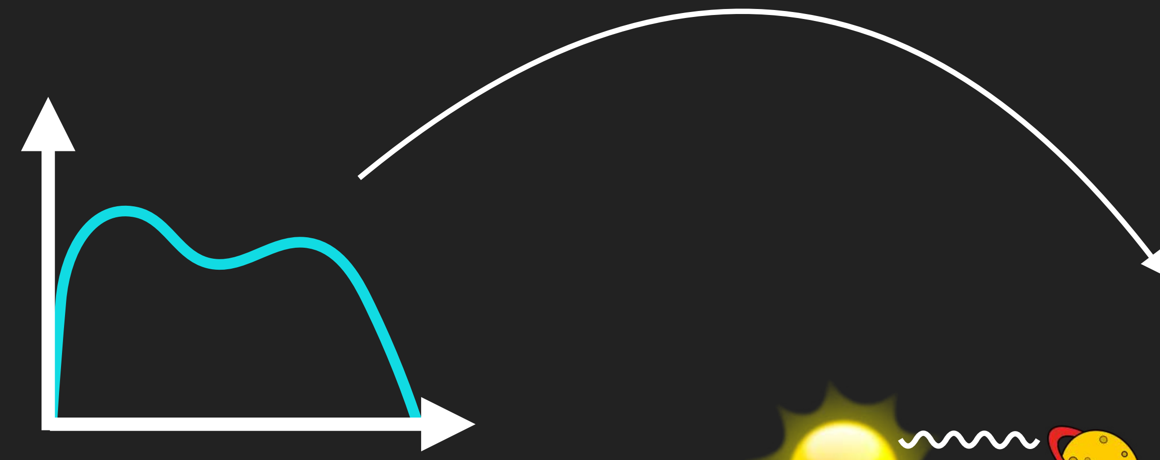


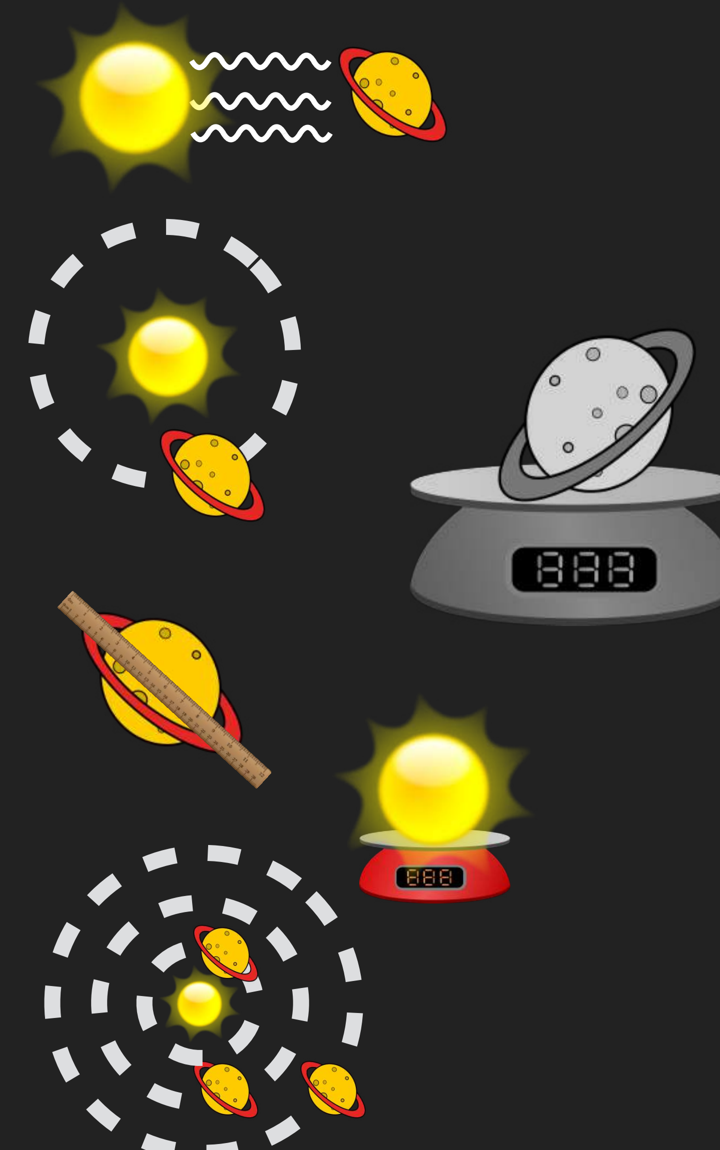
NEURAL NETWORK

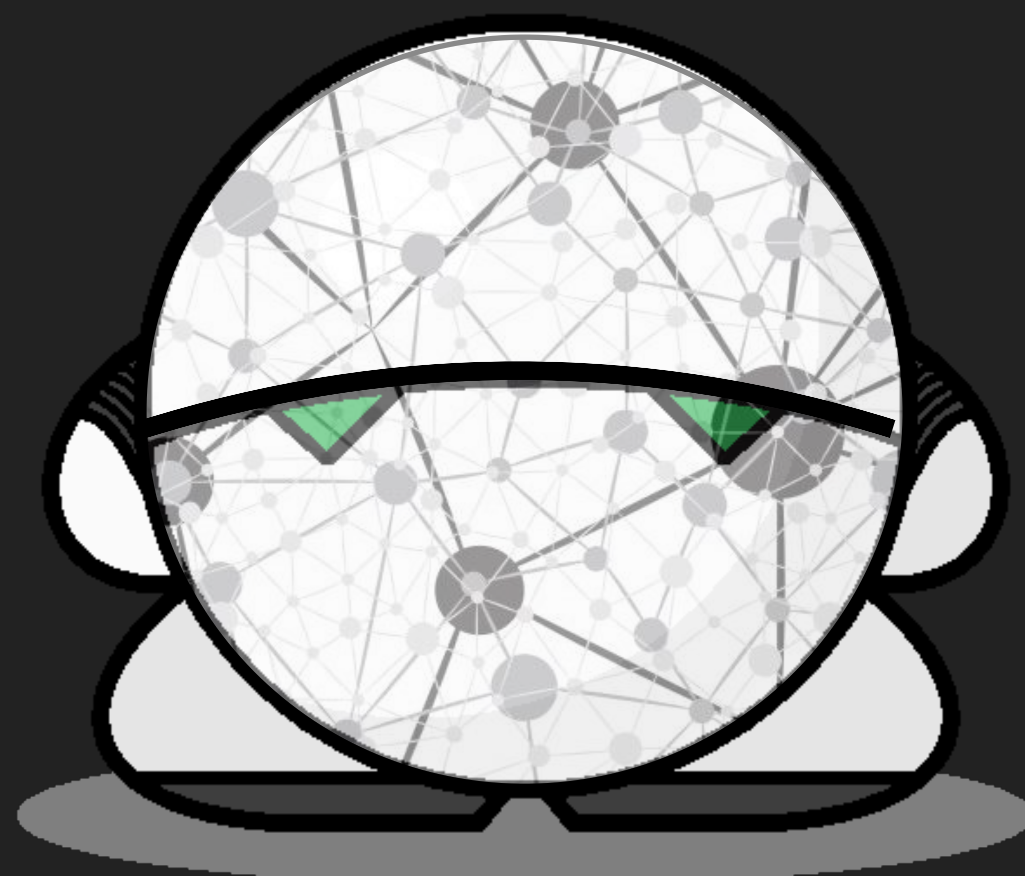


#ALTPLANET

… or generate just one missing property.





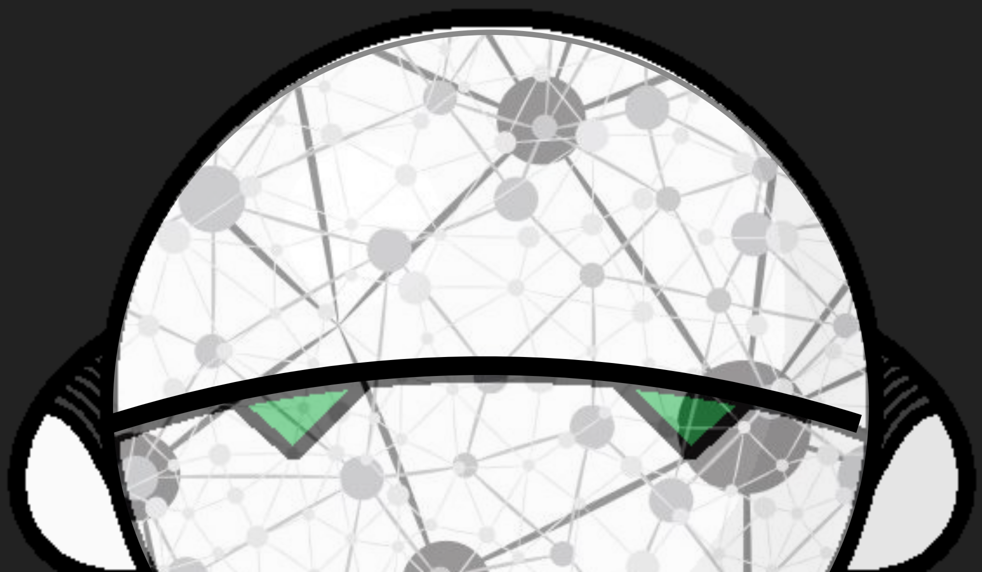


NEURAL NETWORK

DETAILS

(feel free to sleep for the next few slides)

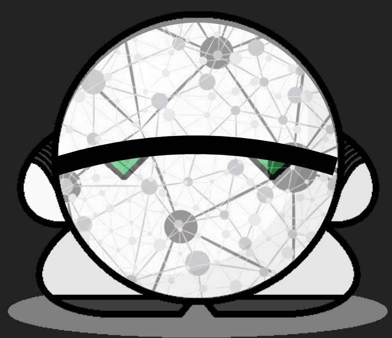
This will all end in tears.
I just know it.



Small print

Require complete property set for a group of planets for network training:

radius, mass, period, equilibrium temperature, number of planets in system, stellar mass

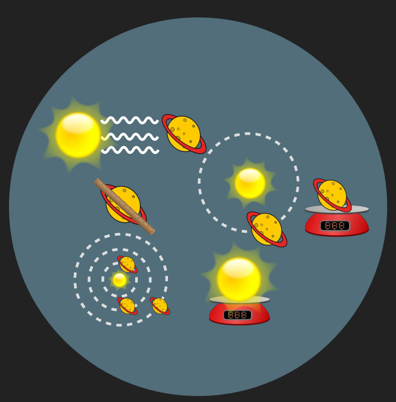


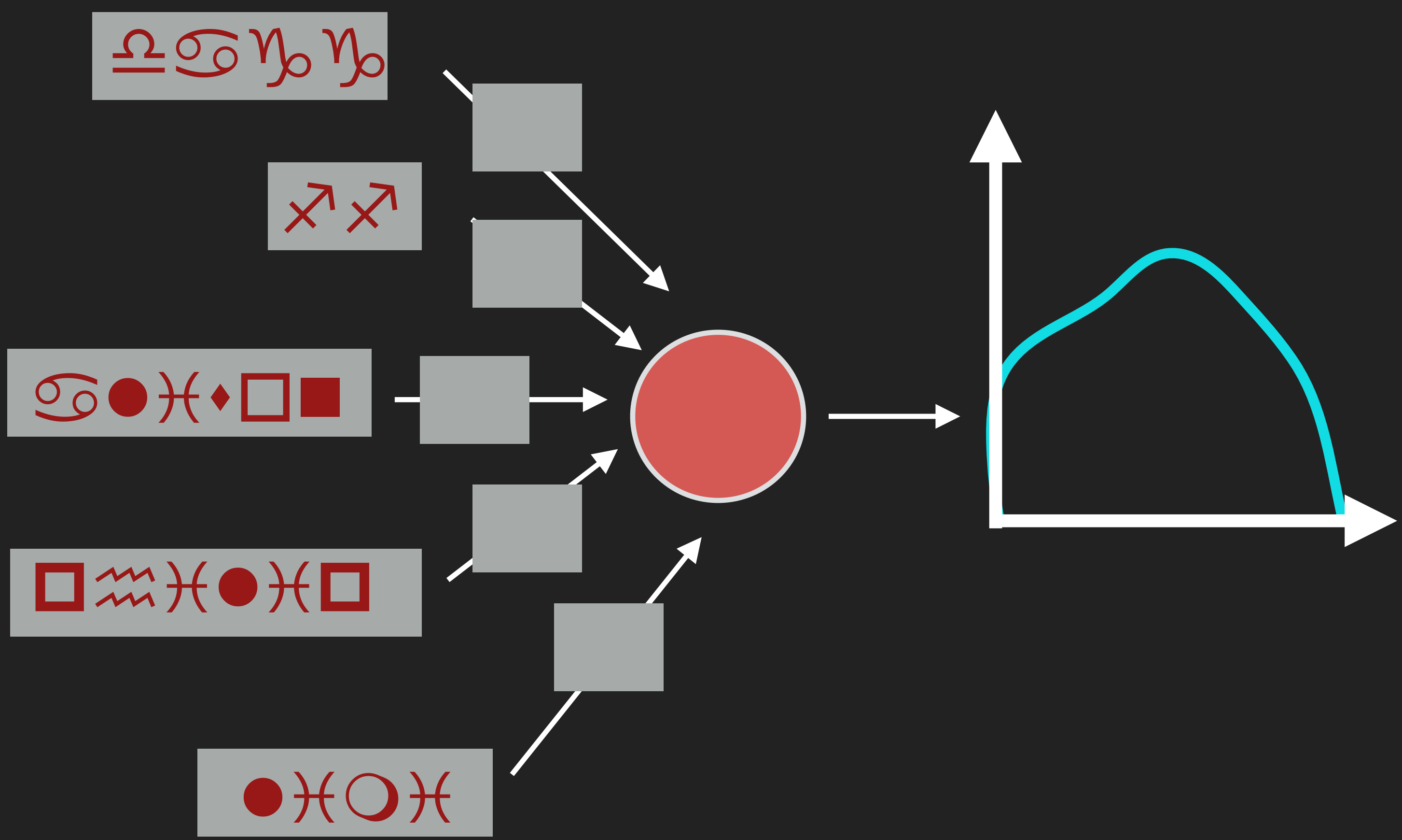
Modified boltzmann machine

Create statistical distribution by representing each planet's properties as an energy.

TRAINING

Network adjusts features / weights to find a distribution that fits the training set.





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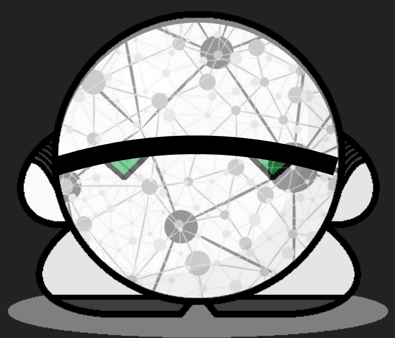

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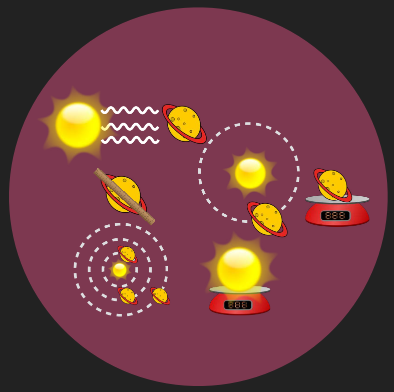

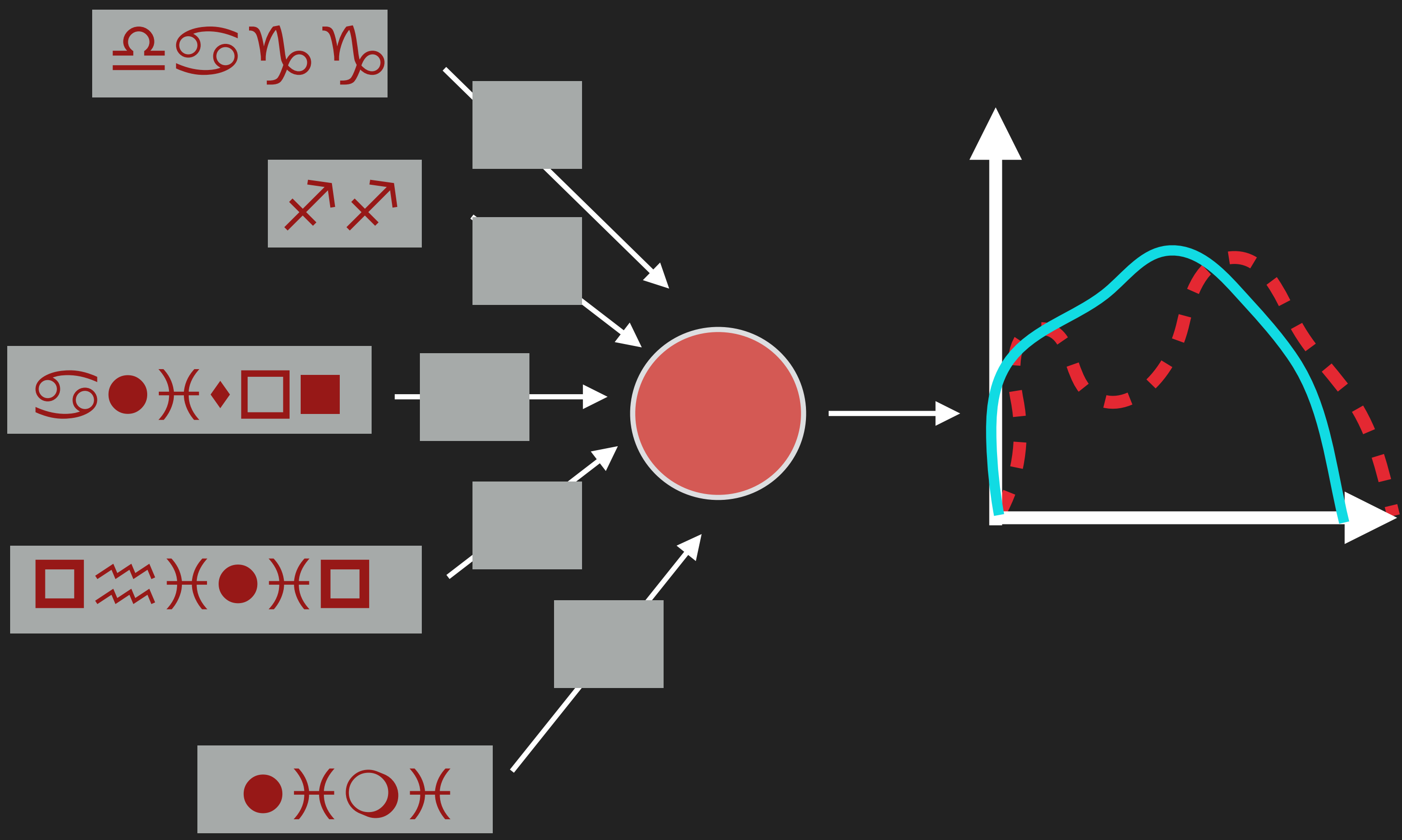

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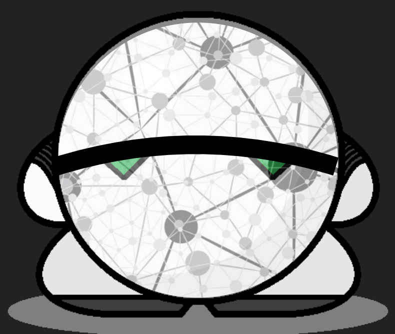

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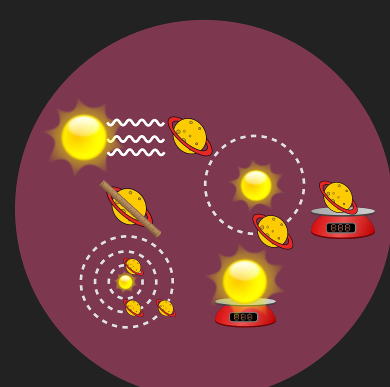

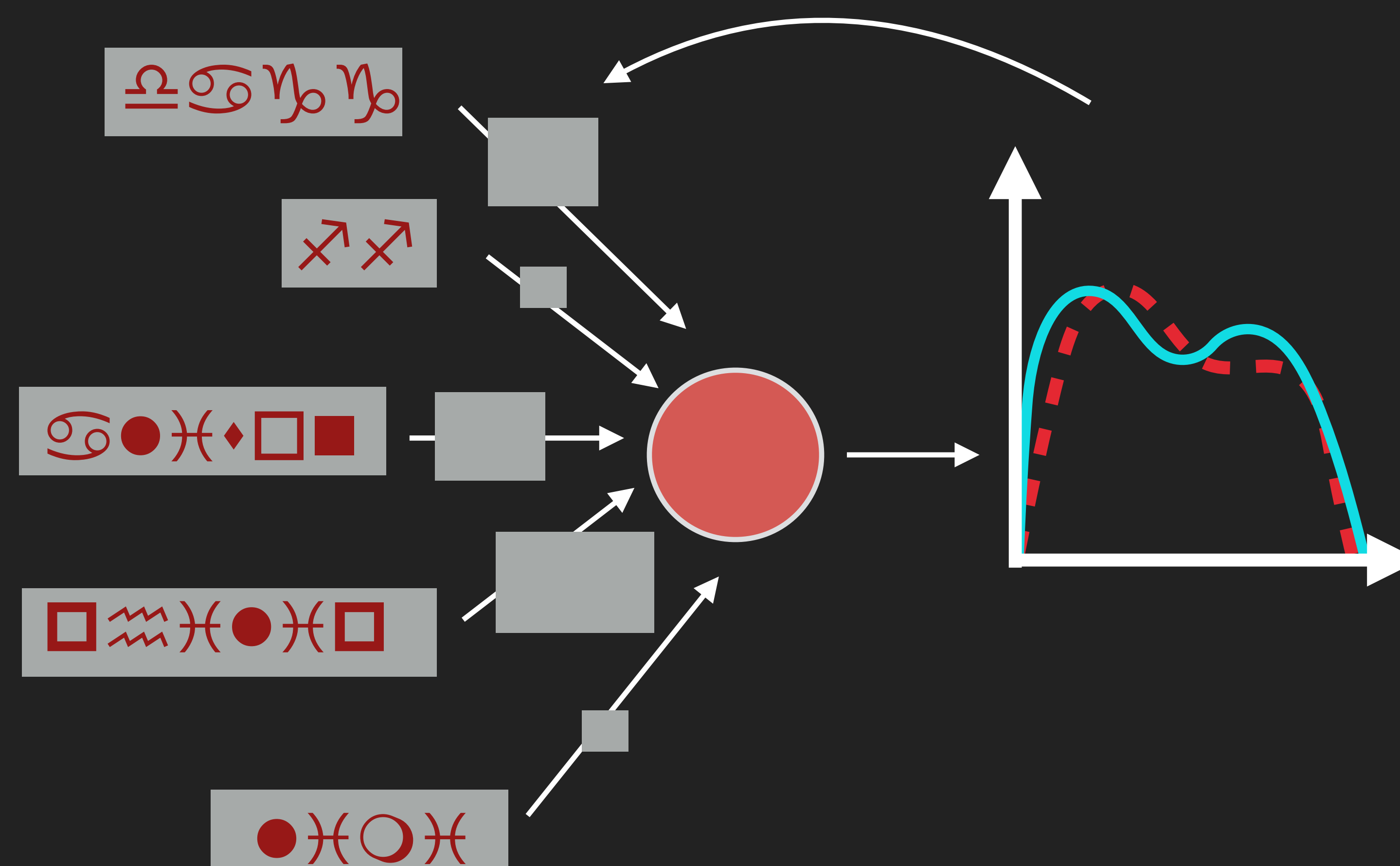

Small print

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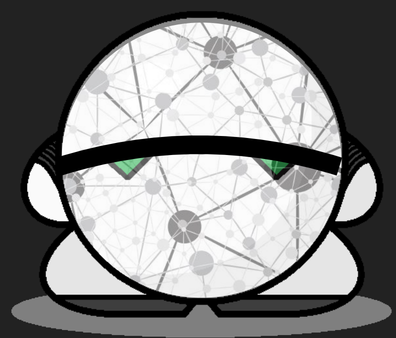
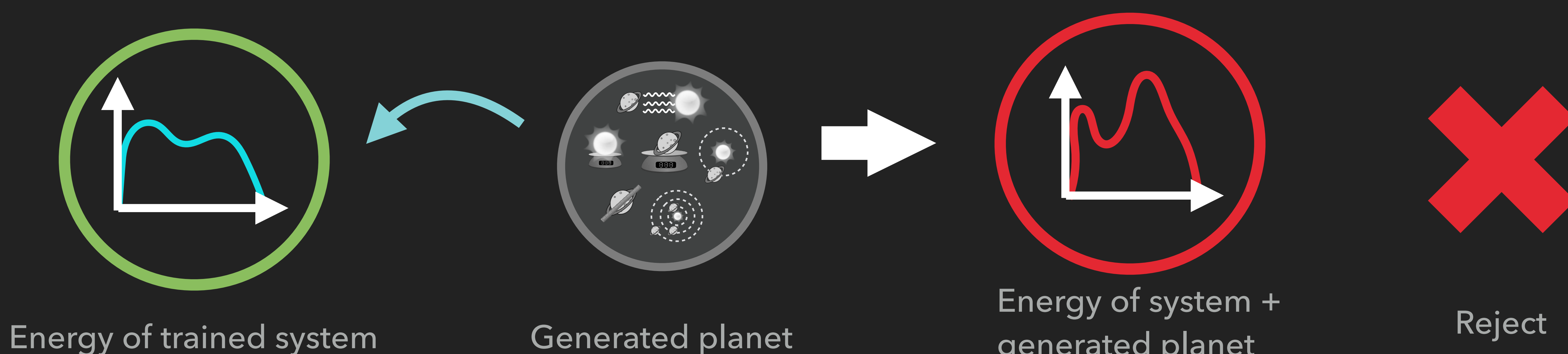


Modified boltzmann machine

Create statistical distribution by representing each planet's properties as an energy.

Monte Carlo

New planet (or planet property) accepted based on the energy difference from adding the planet to the distribution: $P = e^{E_{\mathrm{orig}} - E_{\mathrm{new}}}$



Small print

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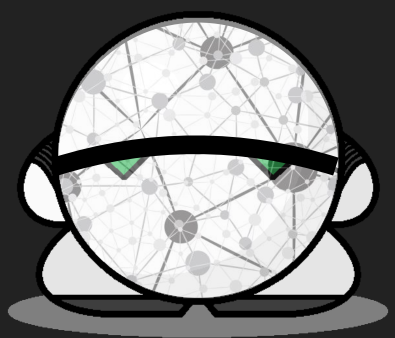

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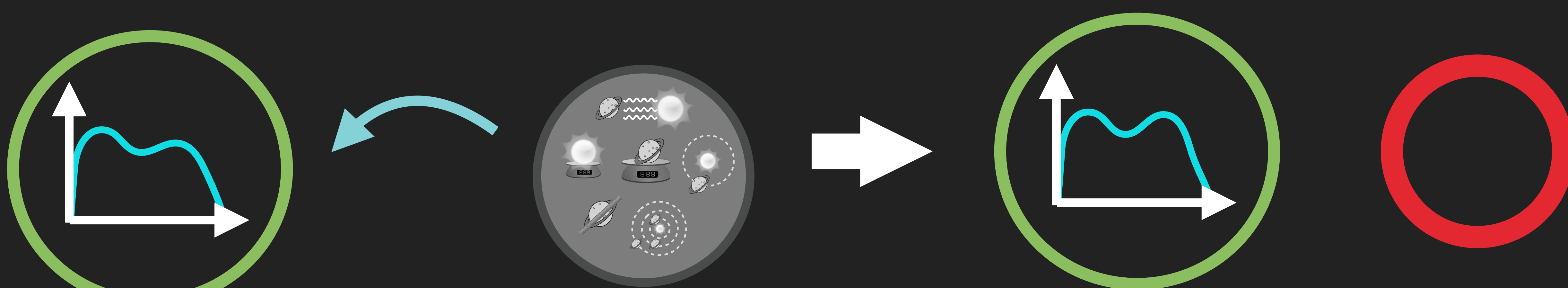

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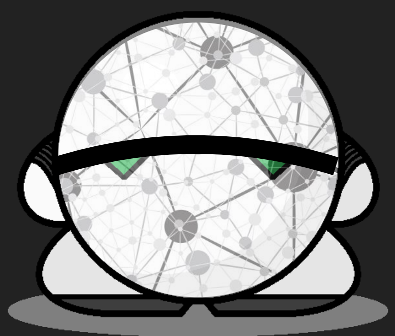

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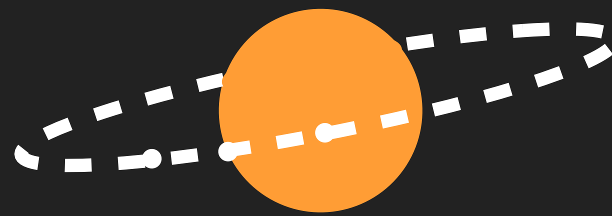
Create statistical distribution by representing each planet's properties as an energy.

Monte Carlo

New planet (or planet property) accepted based on the energy difference from adding the planet to the distribution: $P = e^{E_{\mathrm{orig}} - E_{\mathrm{new}}}$

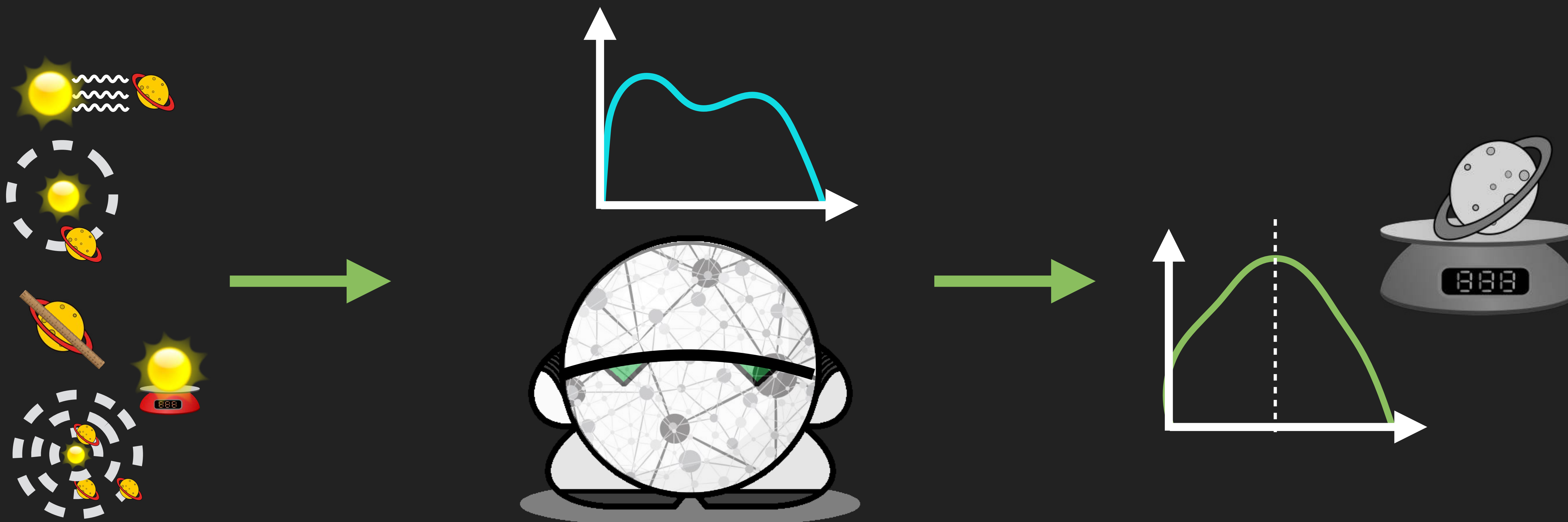
Property distribution

Create multiple (1000) values per planet and take the mean.



Assume you found a transiting planet

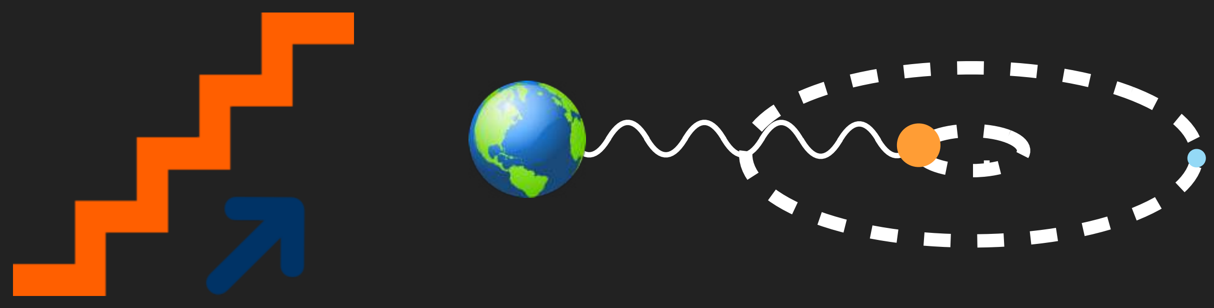
(Radius, no minimum mass)

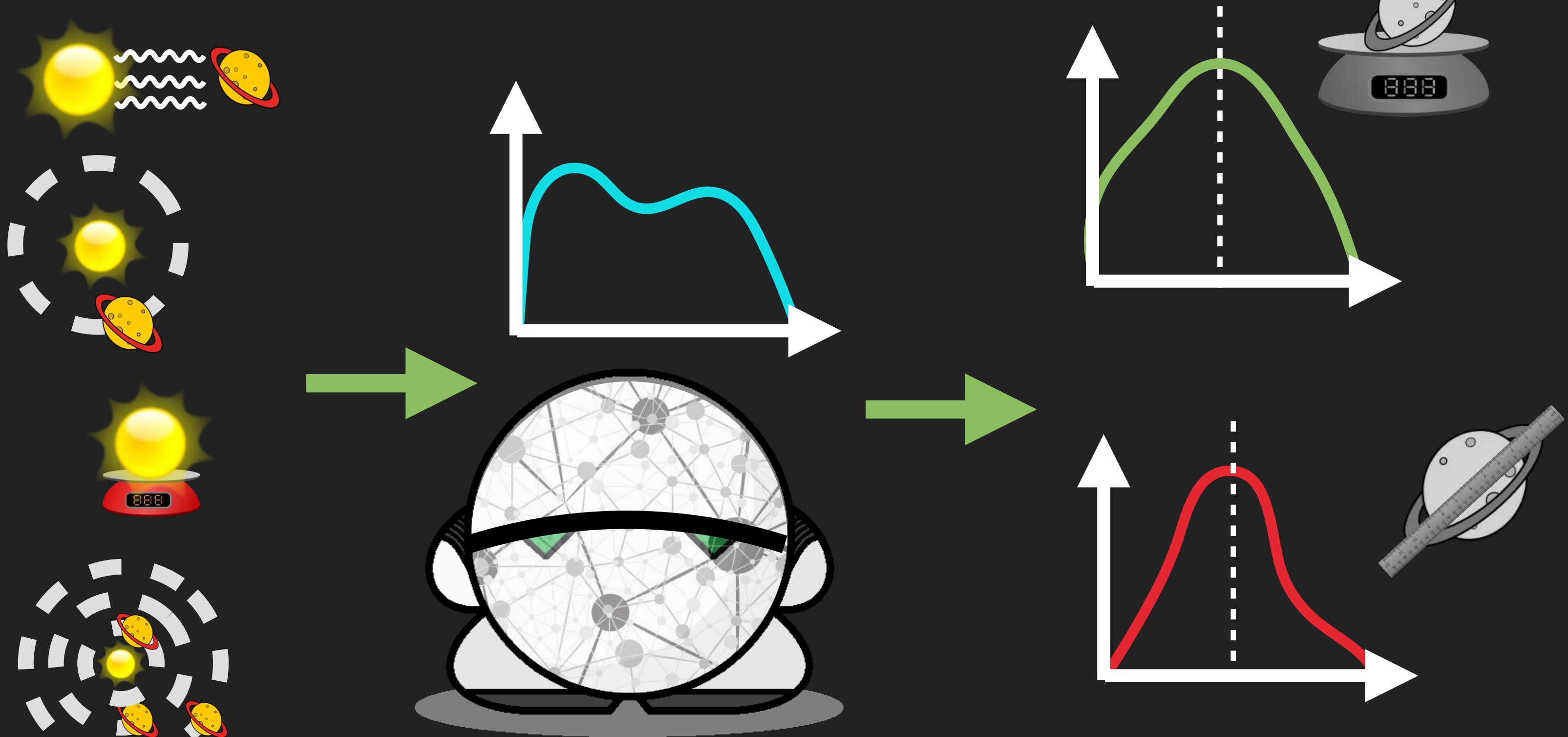


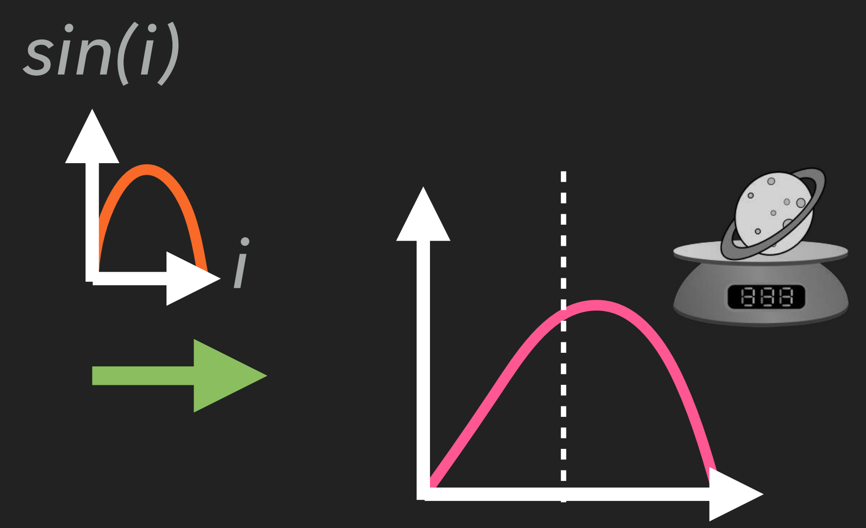
Give the (trained) neural network 5 measured properties

Outputs a distribution of possible mass values

Assume you found a RV planet
(minimum mass, no radius)







Combine with possible masses based on m sin(i)

(Assuming random i)

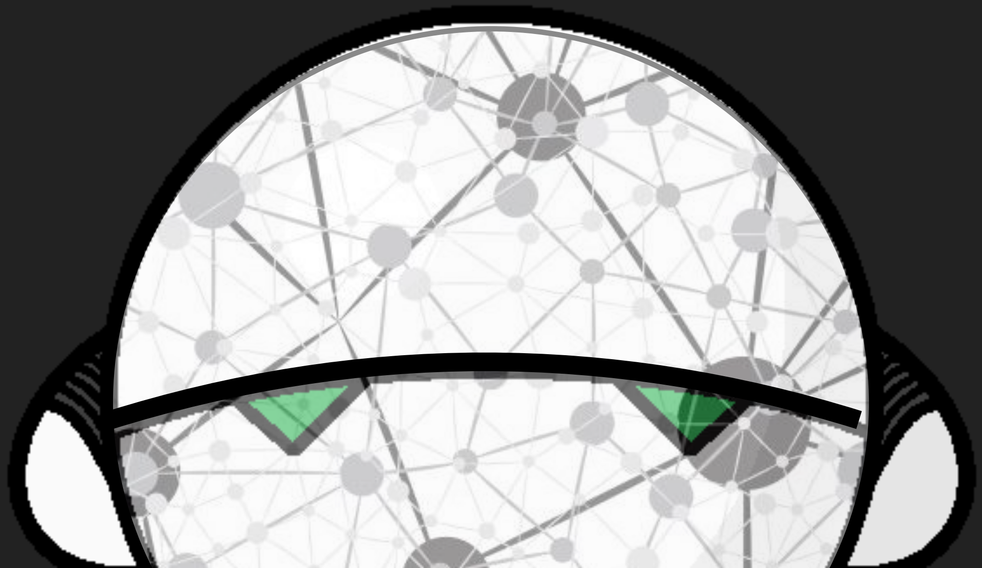
Give the (trained) neural network 4 measured properties

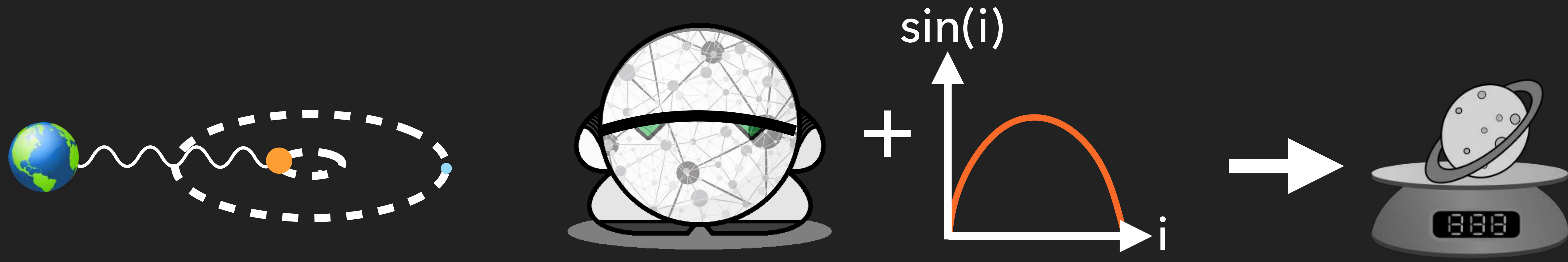
Outputs distribution of possible mass & radius values

RESULTS

(wake up!)

Incredible… it's even worse than I thought it would be.

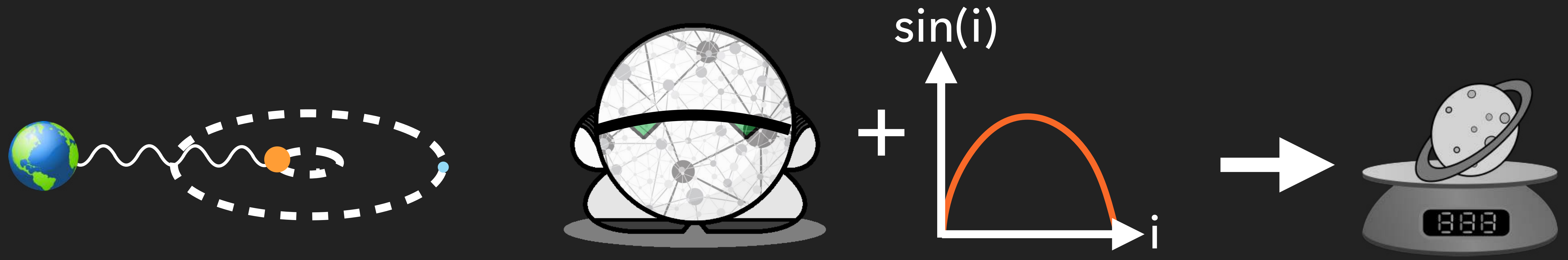




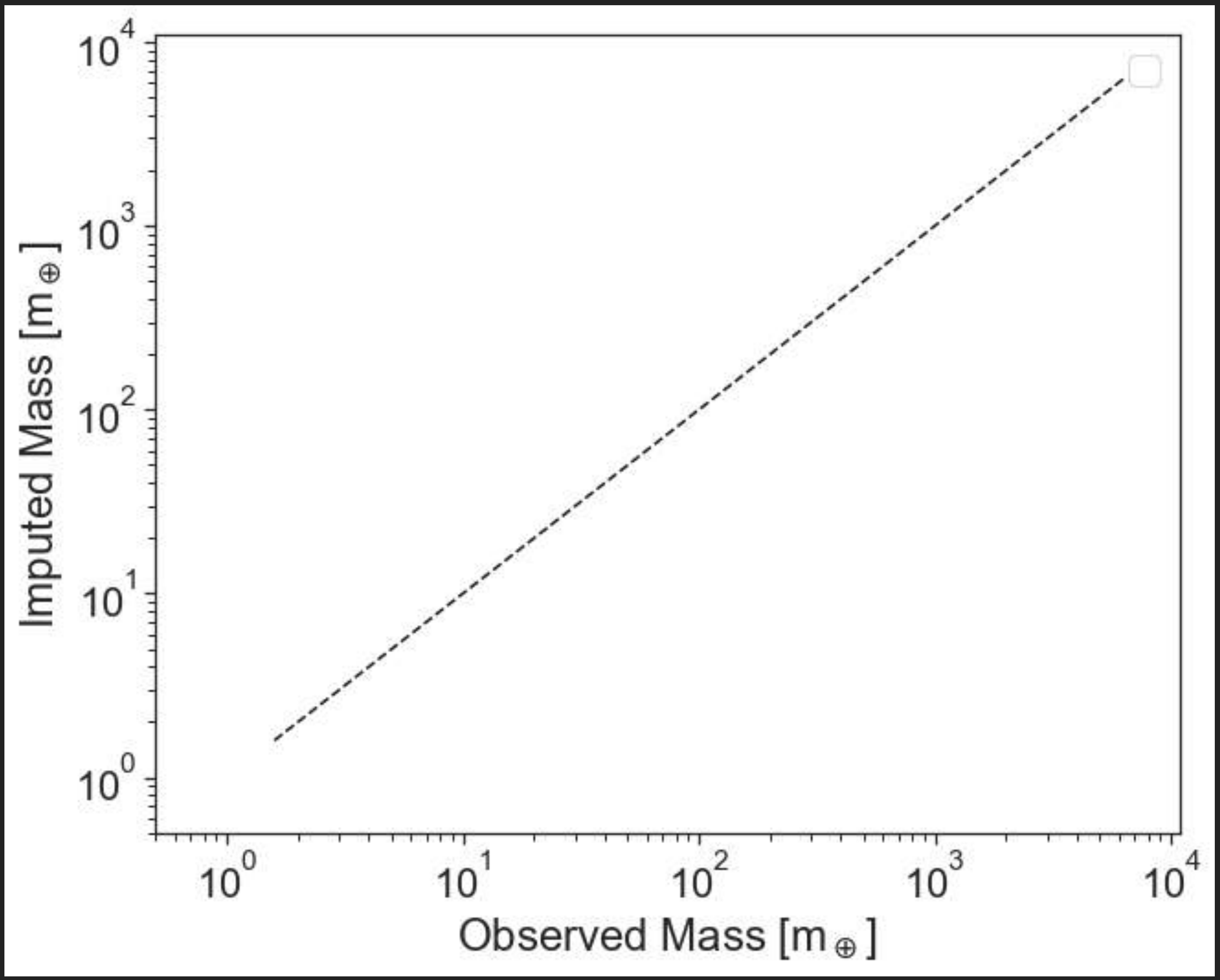
Test results! RV planets

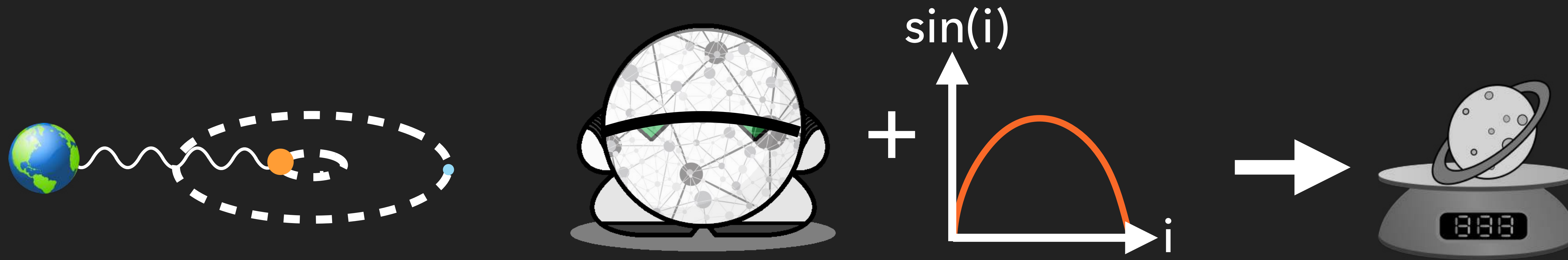
(pretend we only know m sin(i) and look at network generated masses)

(secretly do know the mass of these planets)

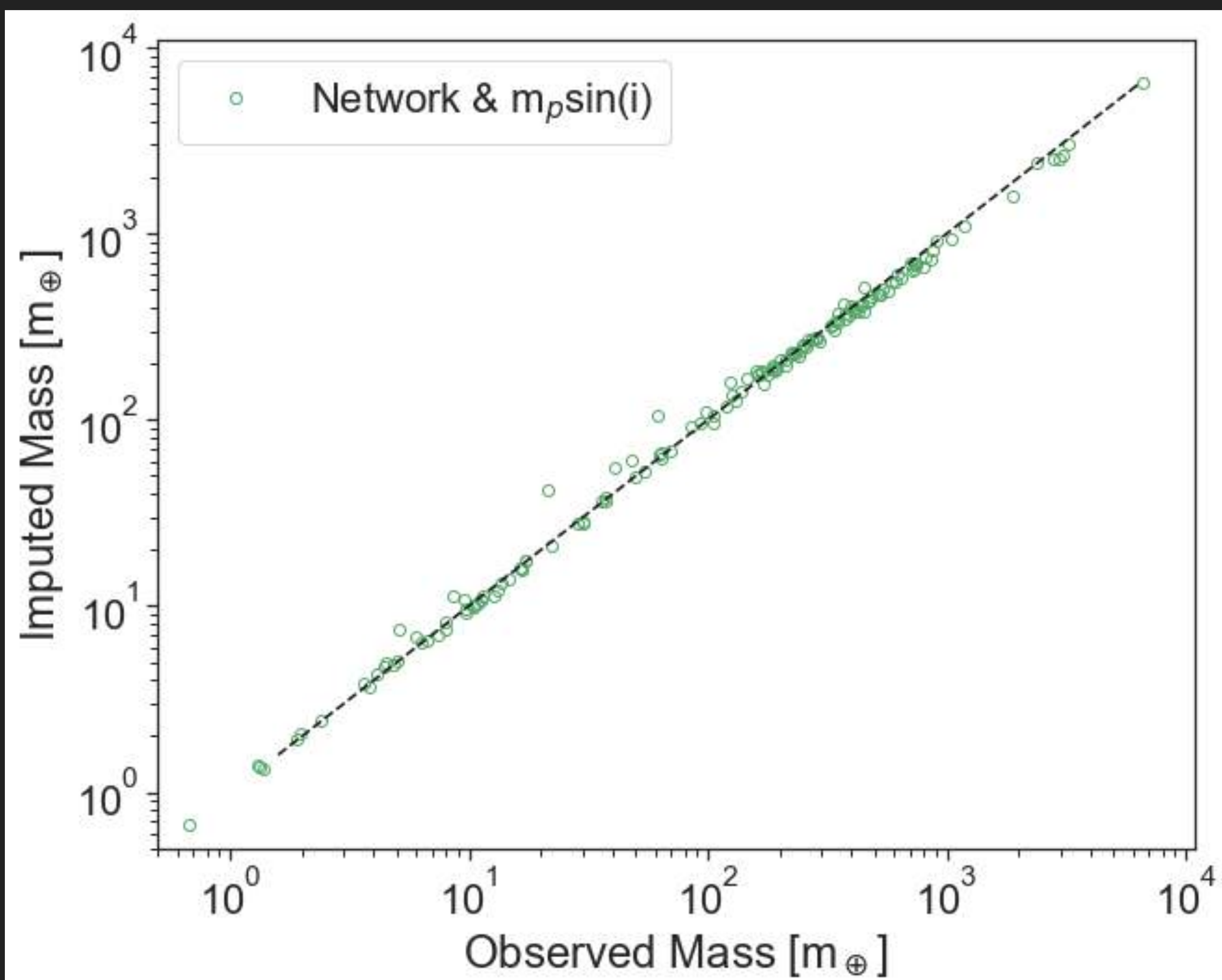


Test results! RV planets



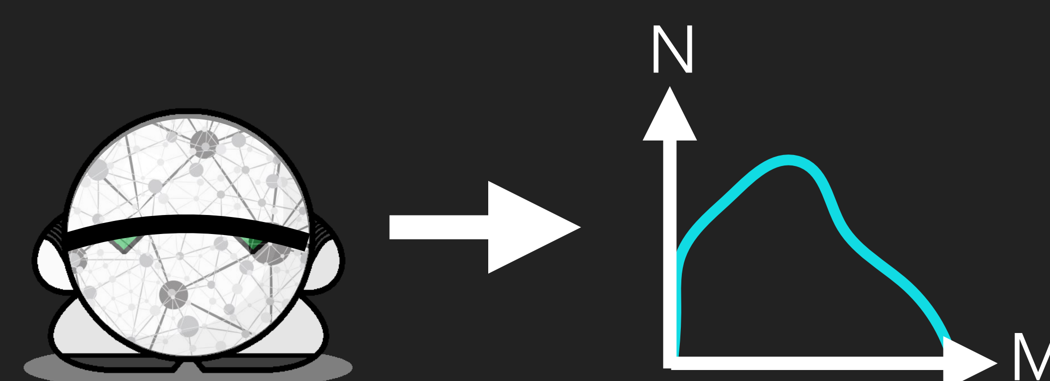


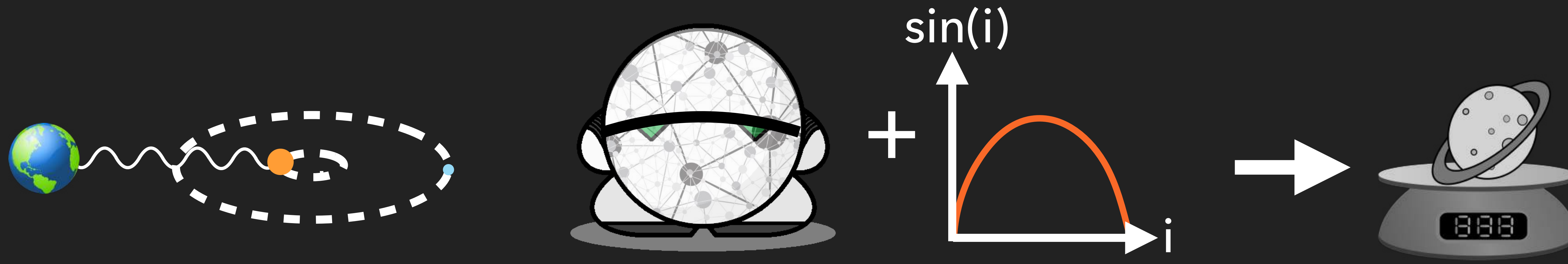
Test results! RV planets



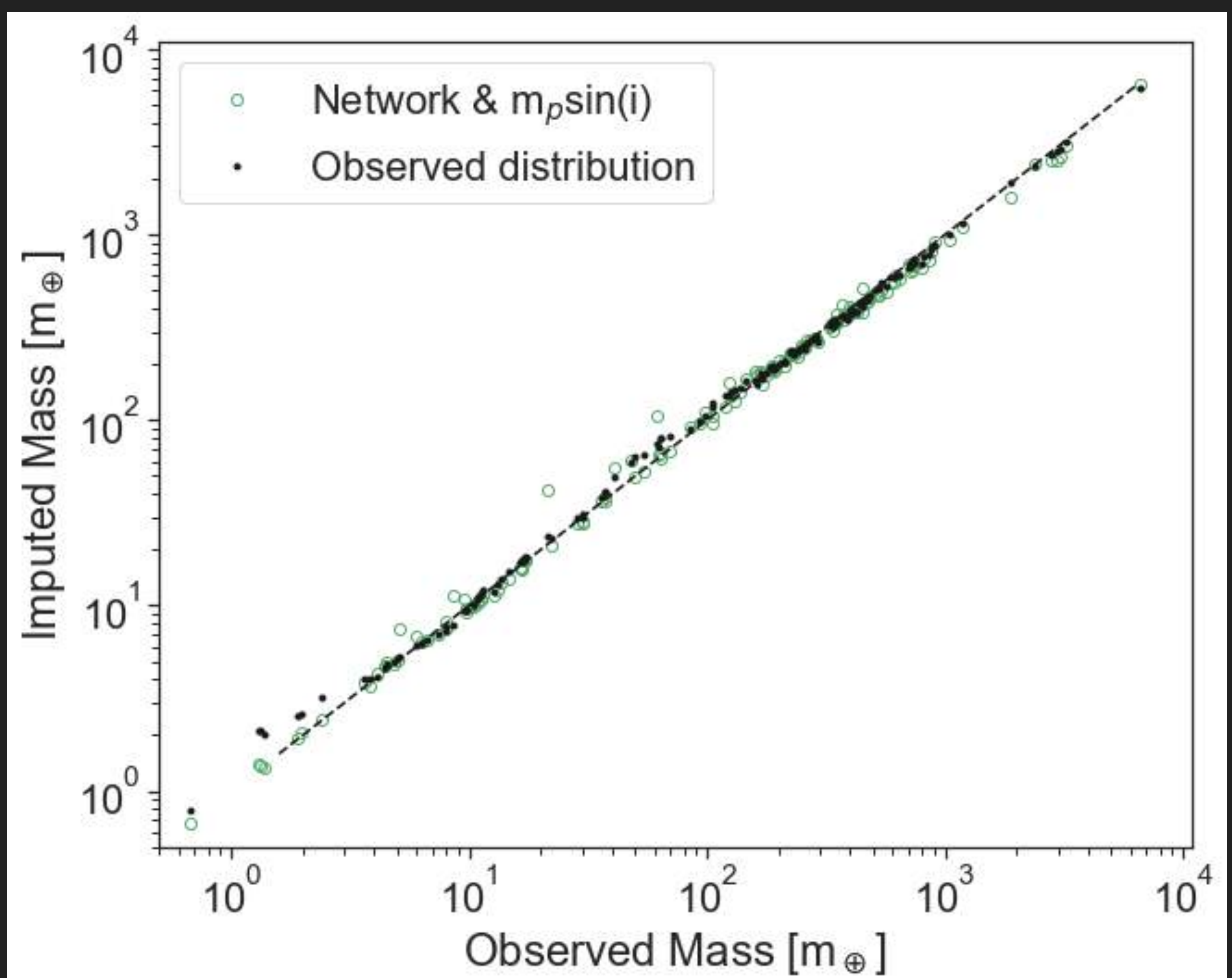
What can we compare this to?

Switch network distribution for the distribution of known planet masses



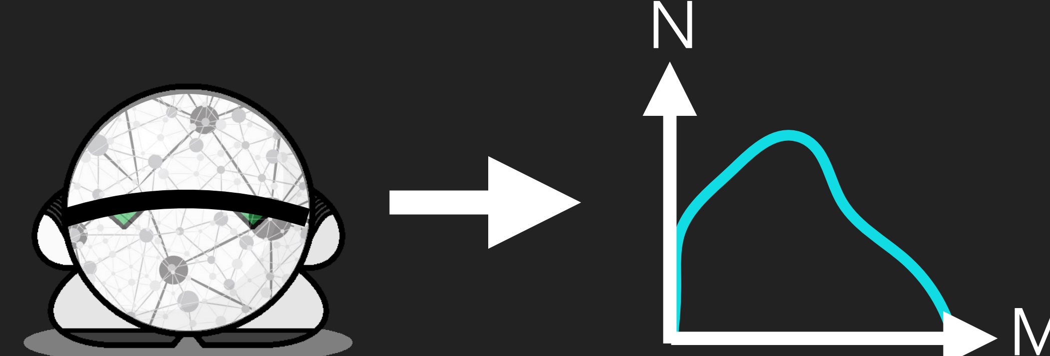


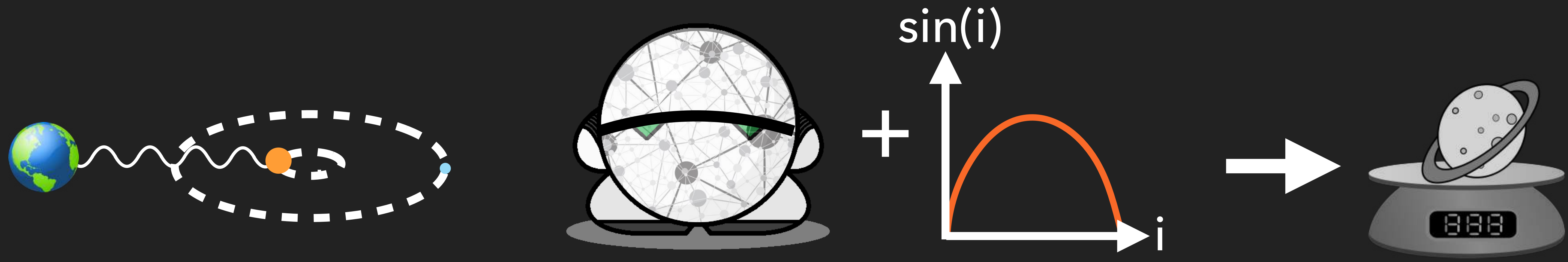
Test results! RV planets



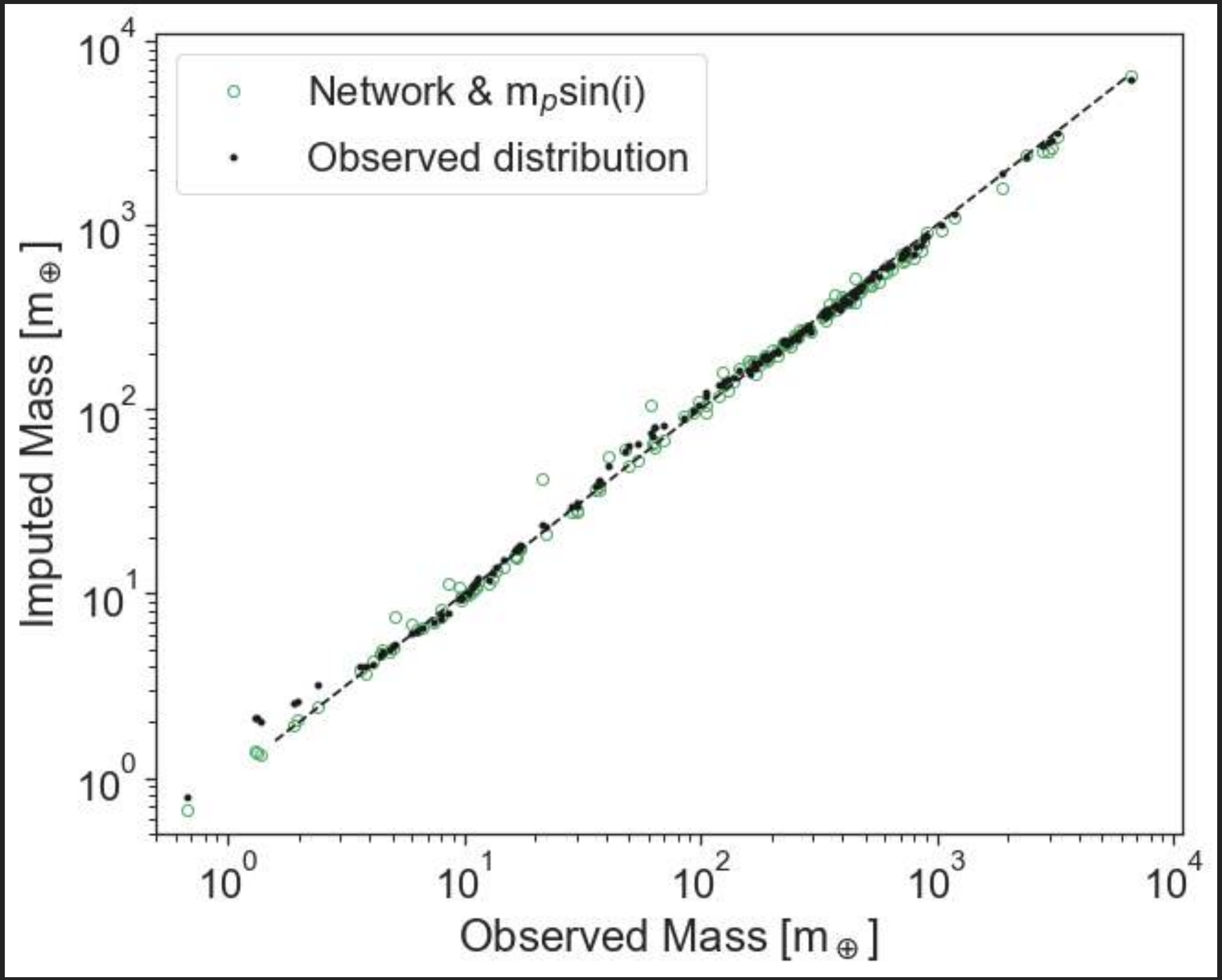
What can we compare this to?

What if we didn't use the network, and just compared m sin(i) to the distribution of known planet masses?





Test results! RV planets

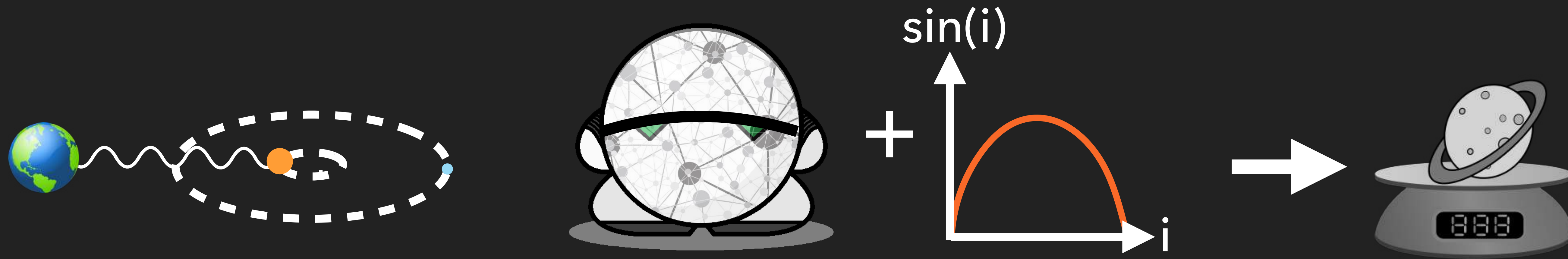


$$\epsilon = \ln(M_{obs}/M_{imputed})$$

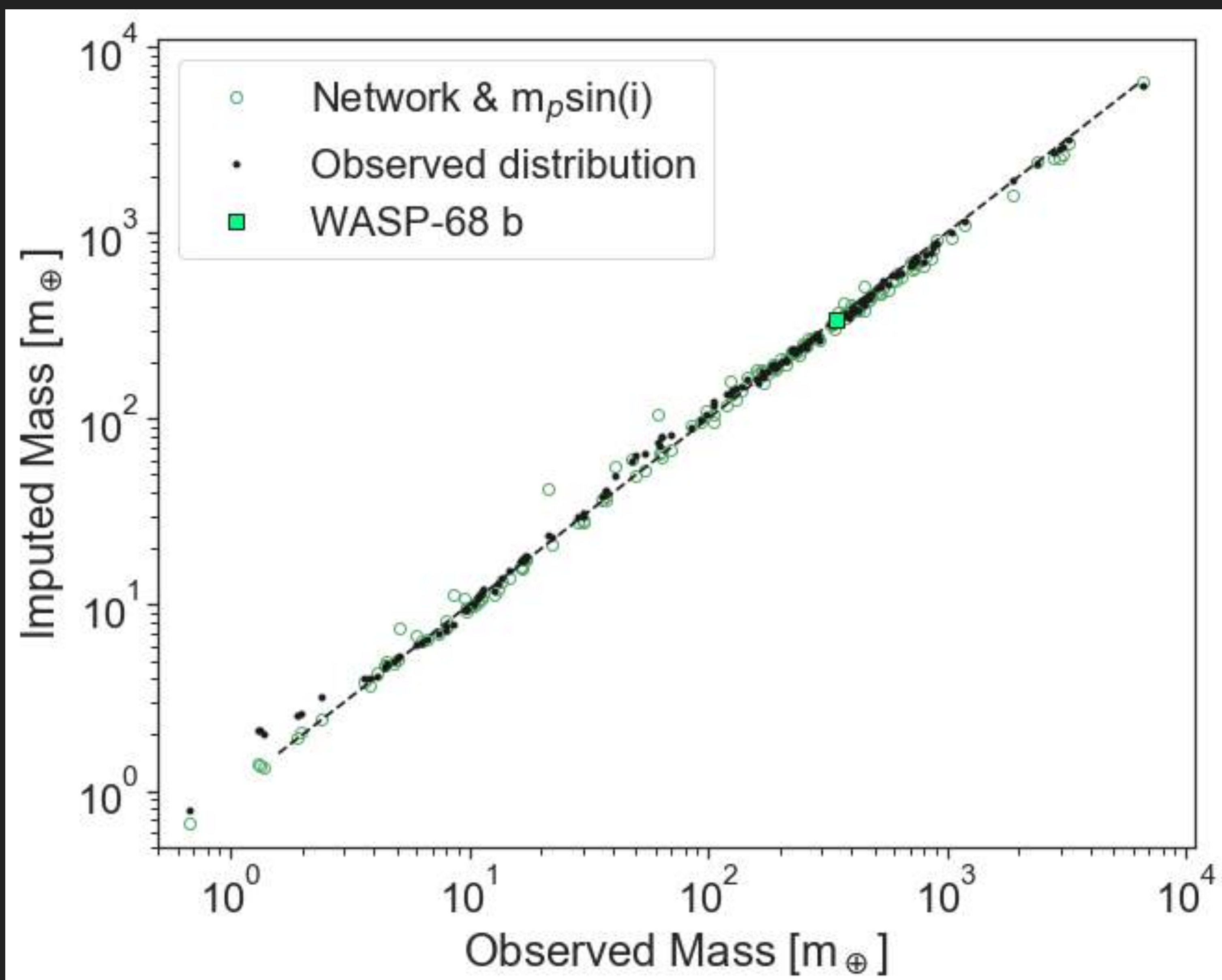
Network error = 0.39

Obs. error = 0.41

On average, network finds a planet mass ~1.5 x true mass



Test results! RV planets

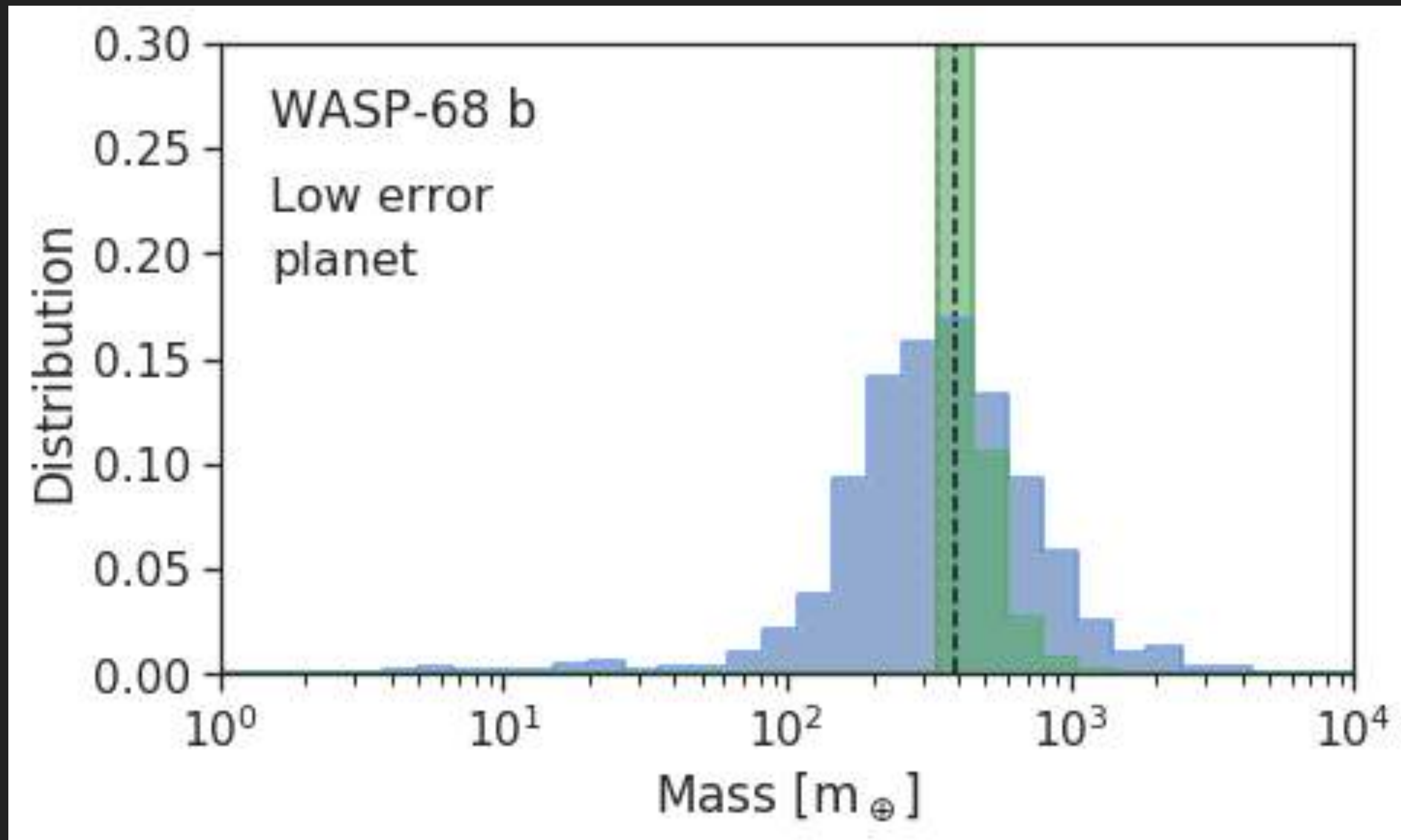


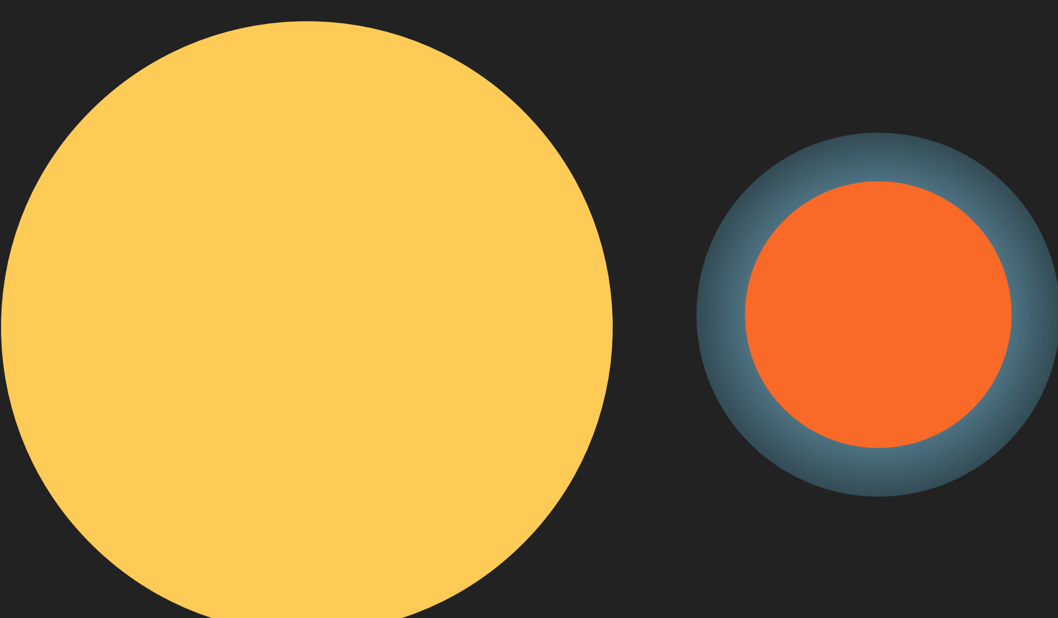
Where do we do well?

WASP-68b has a very low error

What kind of planet is this?

Best Worlds

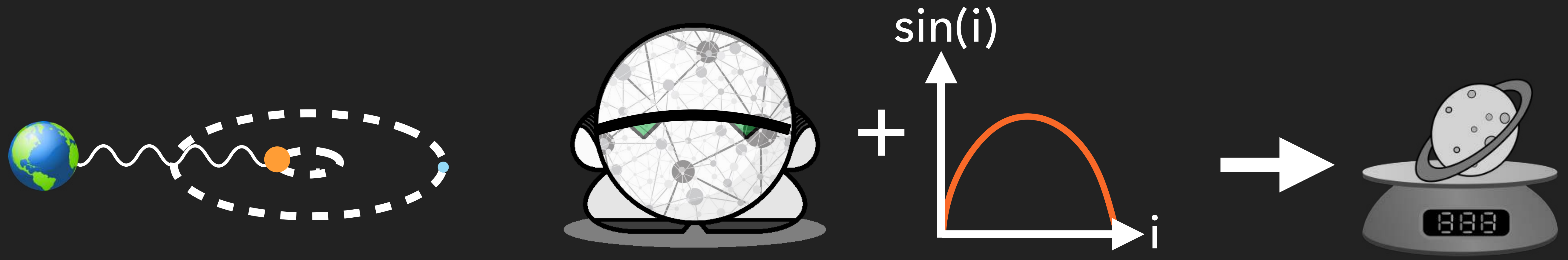




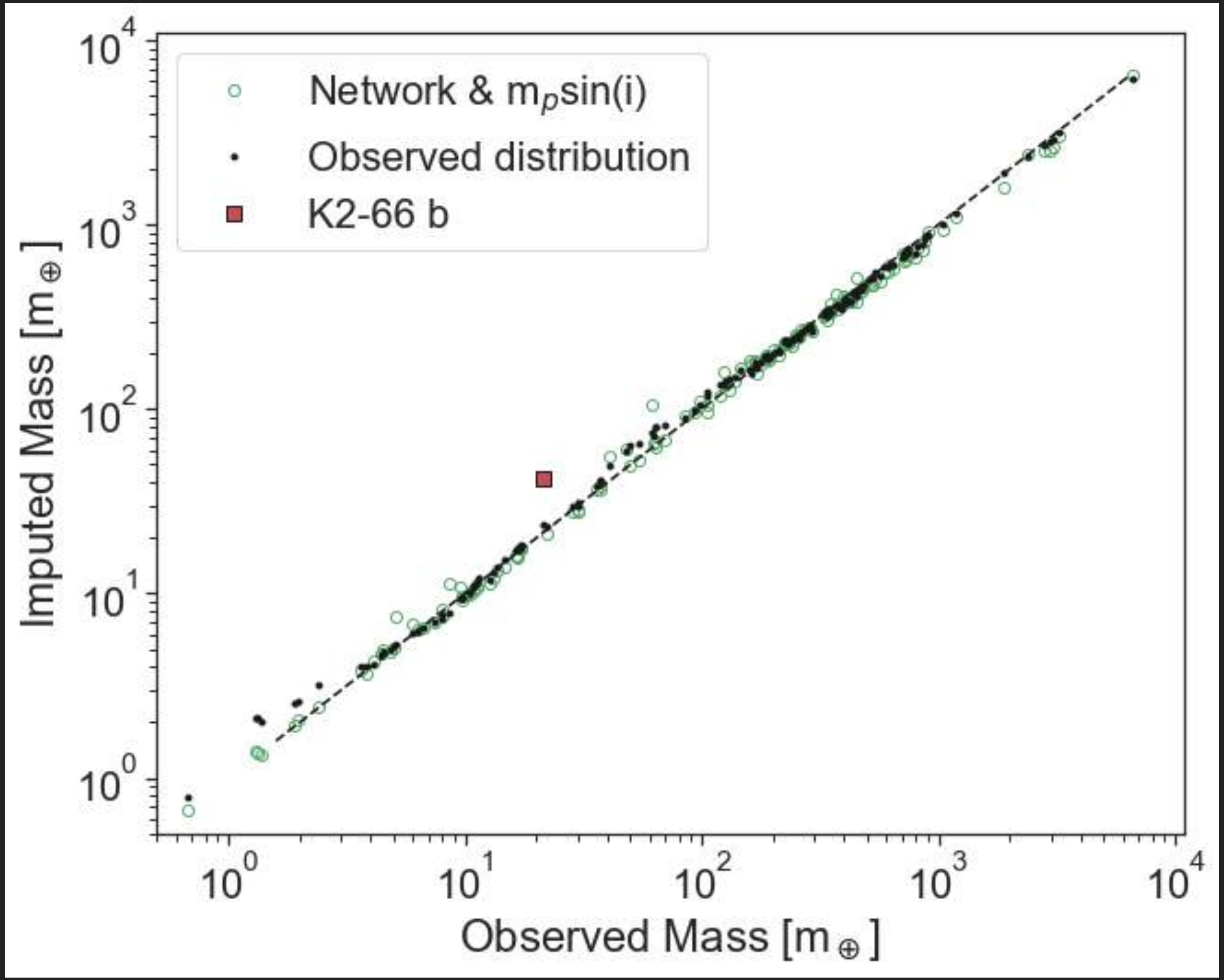
Inflated hot Jupiter

$M = 1.1M_{\mathrm{Jup}}$ $R = 1.32R_{\mathrm{Jup}}$

$P = 5$ days



Test results! RV planets

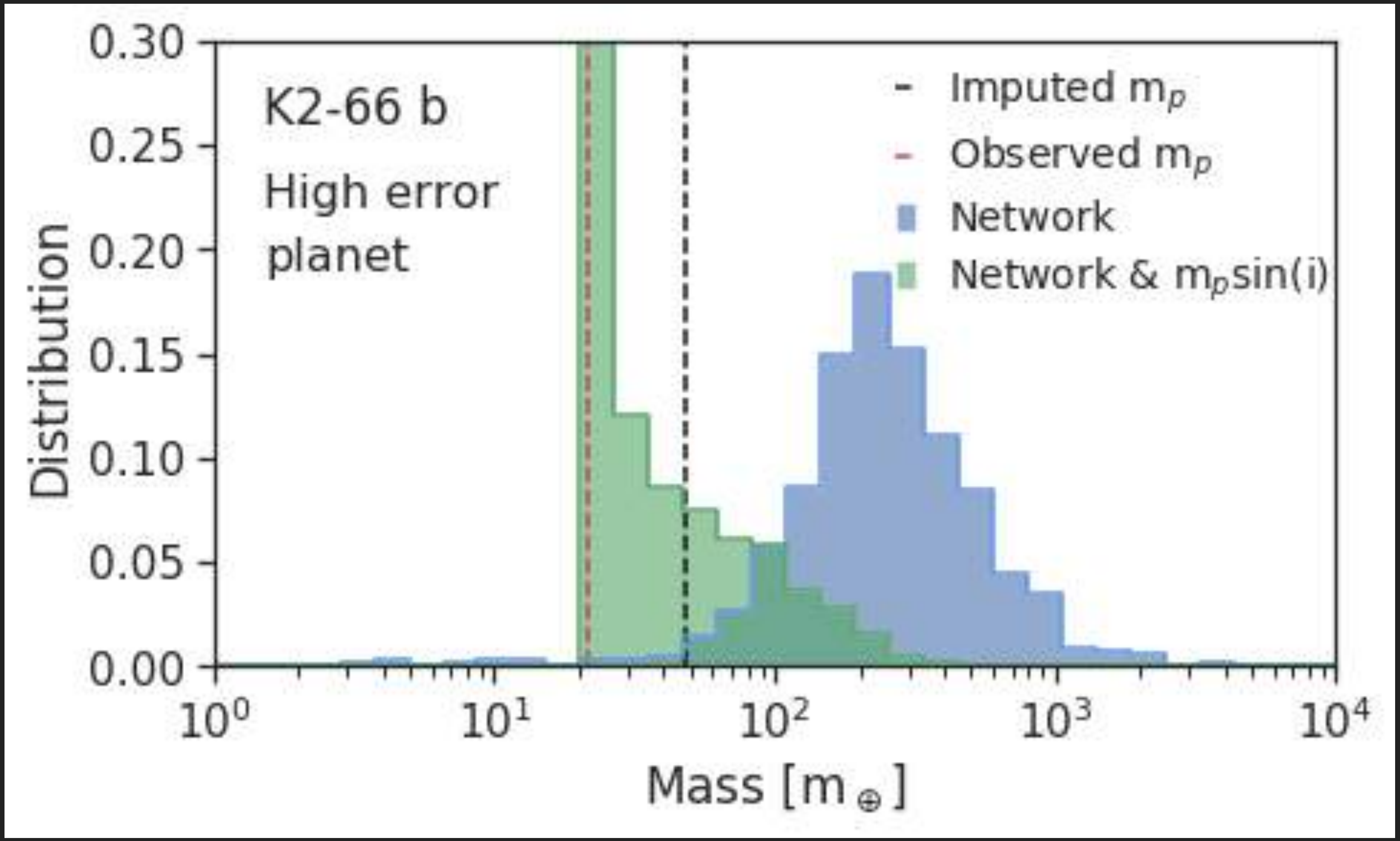


How about the bad planets?

K2-66 b has a high error

What's its problem?!

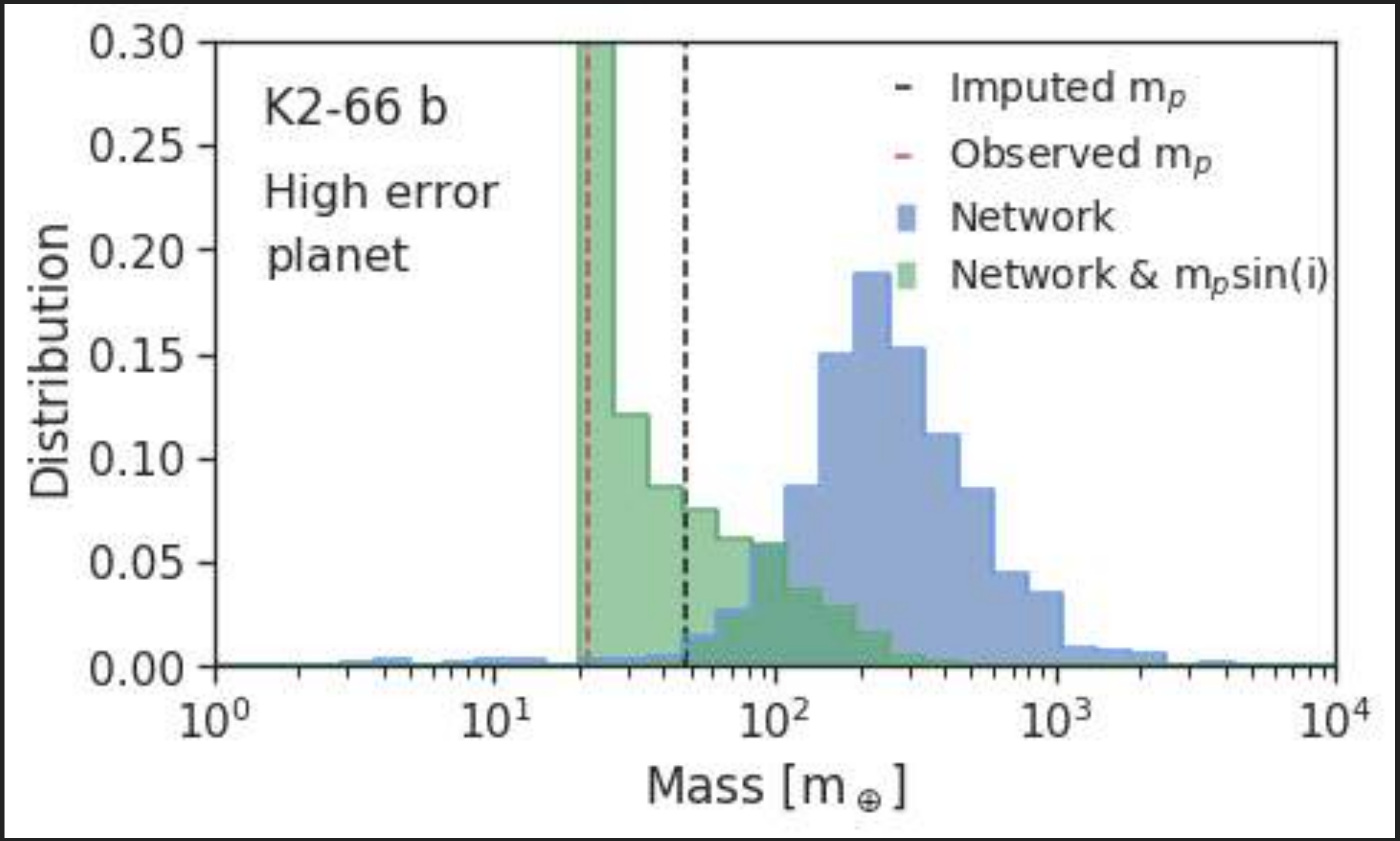
Bad Worlds

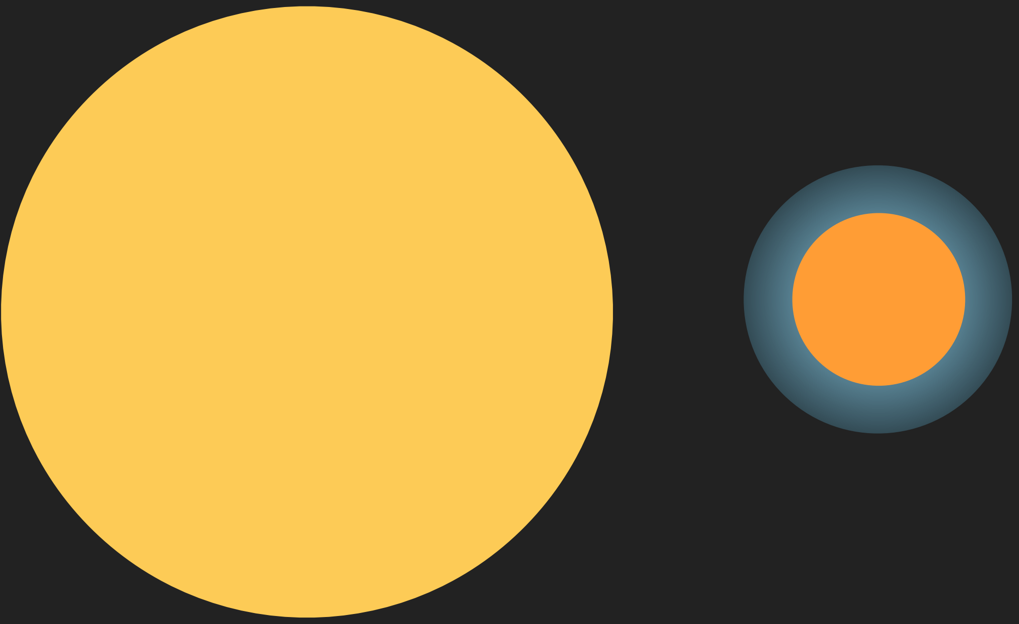


Danger!

If your m sin(i) value lies in the low probability tail of the network distribution, it ***may*** indicate a high error.

Bad Worlds



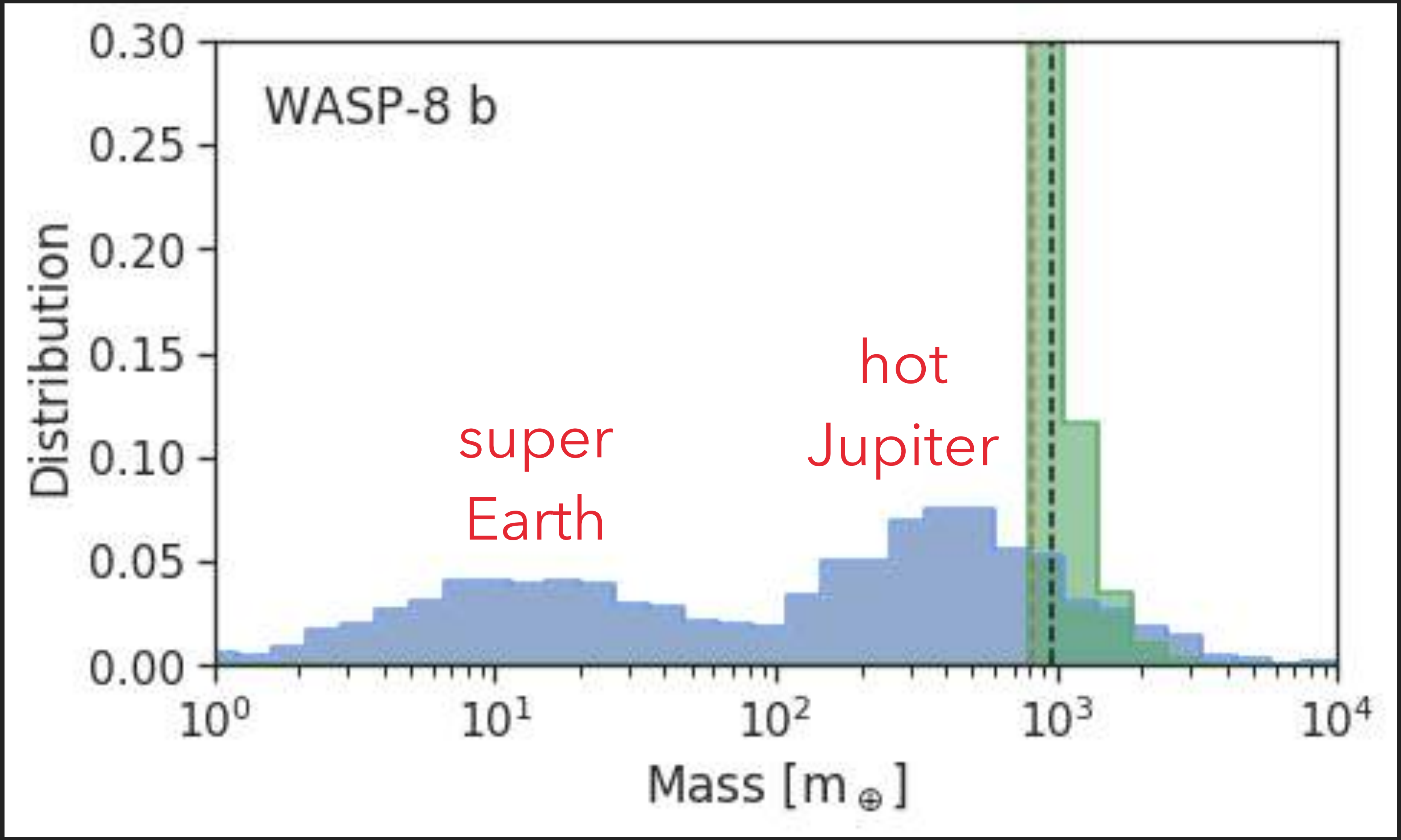


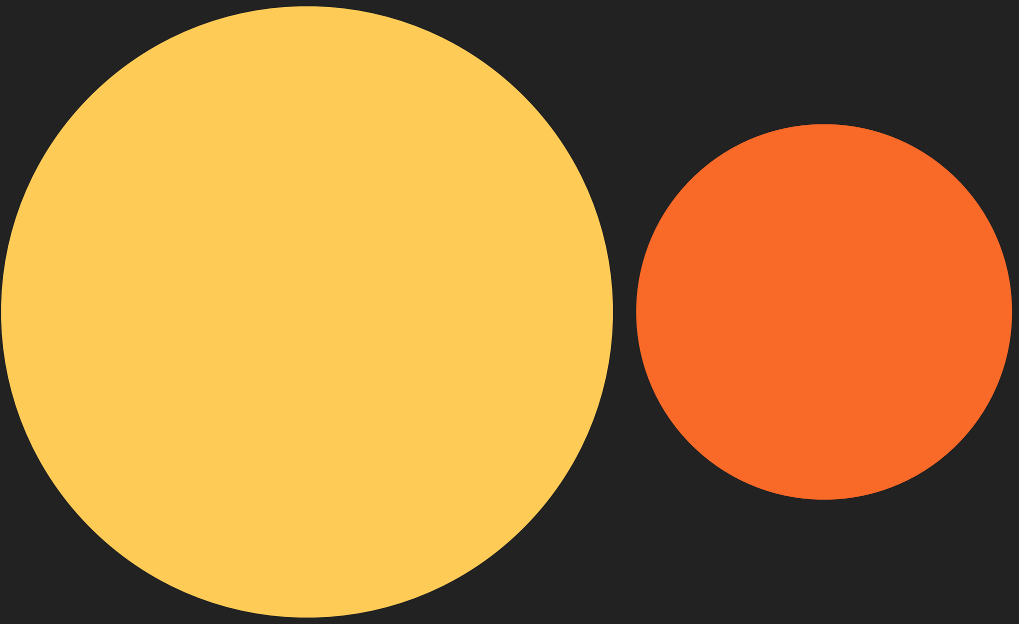
Hot sub-Neptune

$M = 21.3 M_\oplus$ $\quad R = 2.5 R_\oplus$

$P = 5$ days "Photoevaporation dessert"

Curious worlds



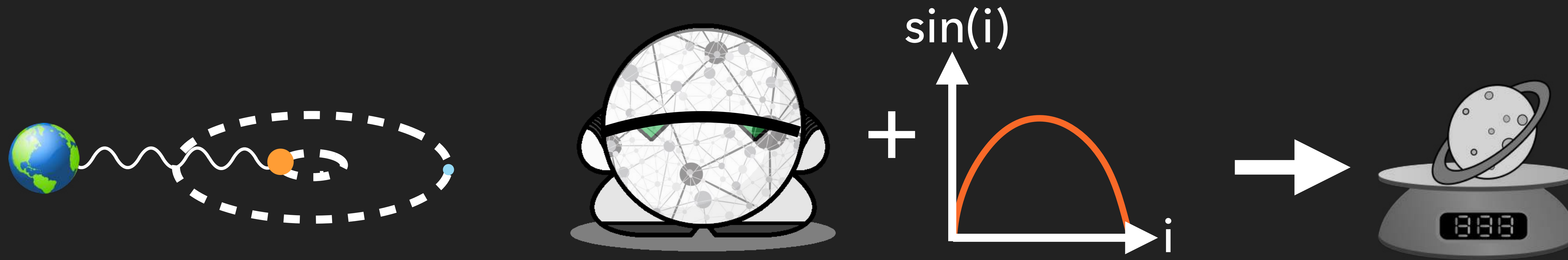


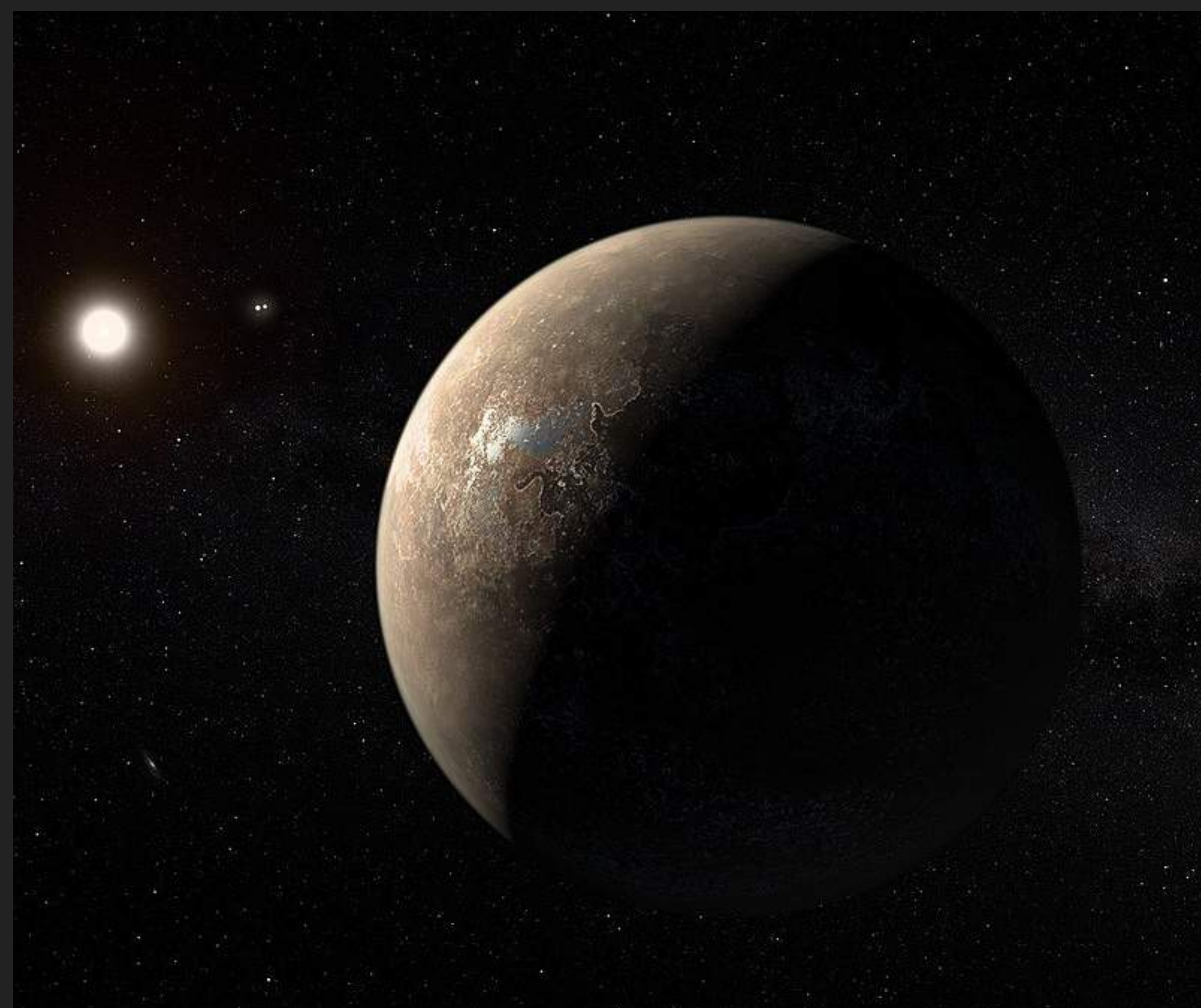
Super-size hot Jupiter

$M = 2.5 M_{\mathrm{Jup}}$ $\quad$ $R = 1.1 R_{\mathrm{Jup}}$

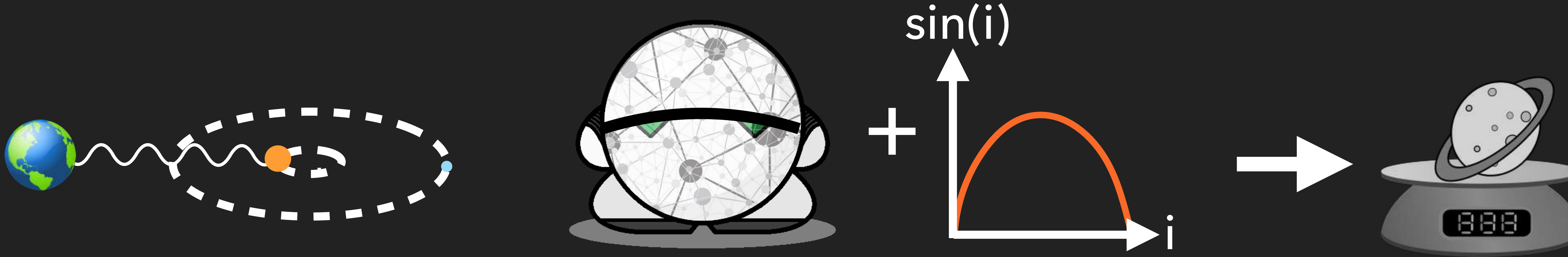
$P = 8$ days

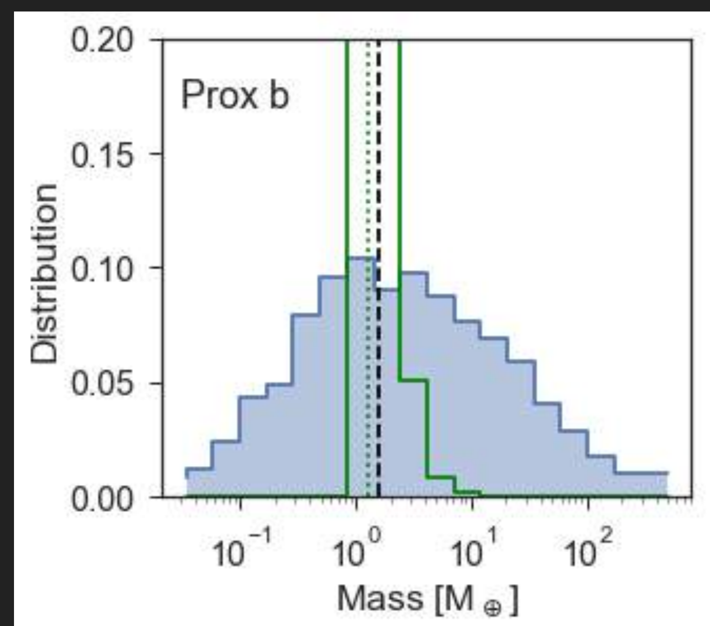
2 statistically consistent options

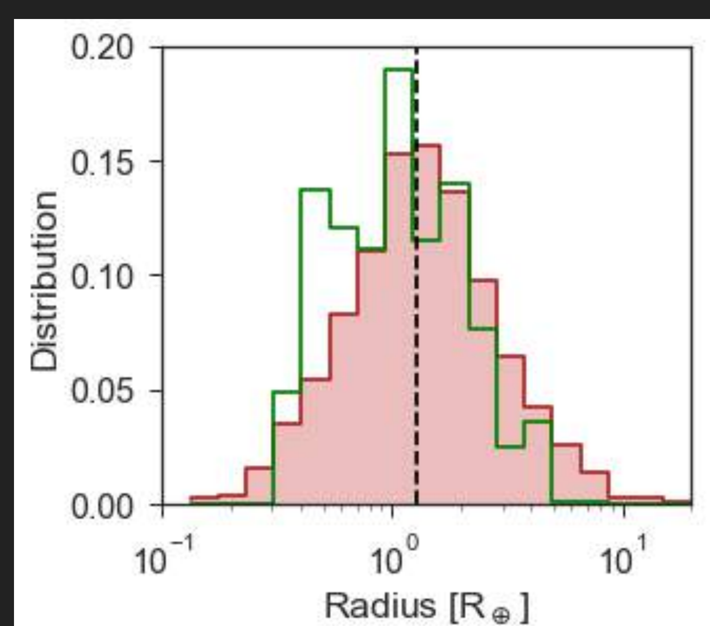




Proxima Centauri-b  ~ 1.3 



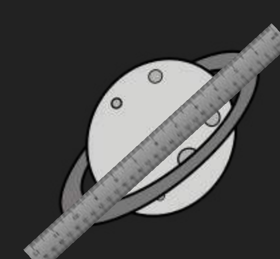




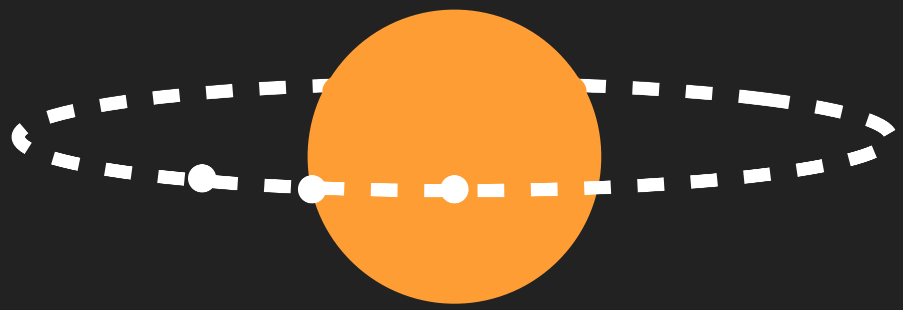
Proxima Centauri-b

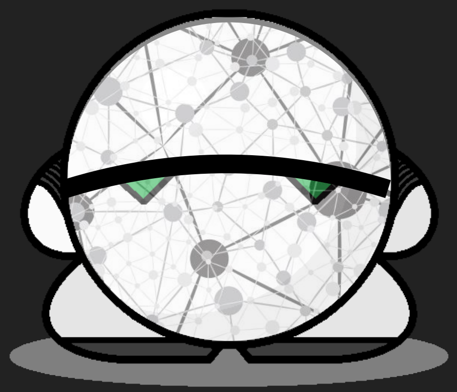
$M \sin(i) \simeq 1.3$

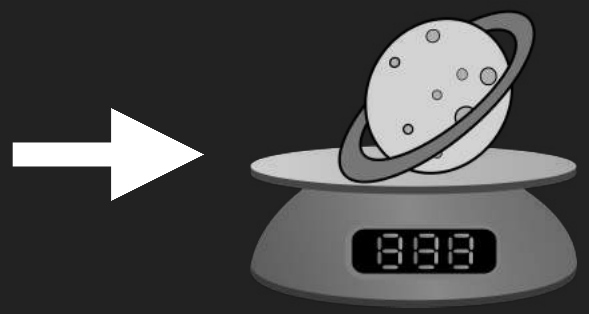
$M \simeq 1.6^{+0.46}_{-0.36}$



$R \simeq 1.3^{+1.2}_{-0.65}$

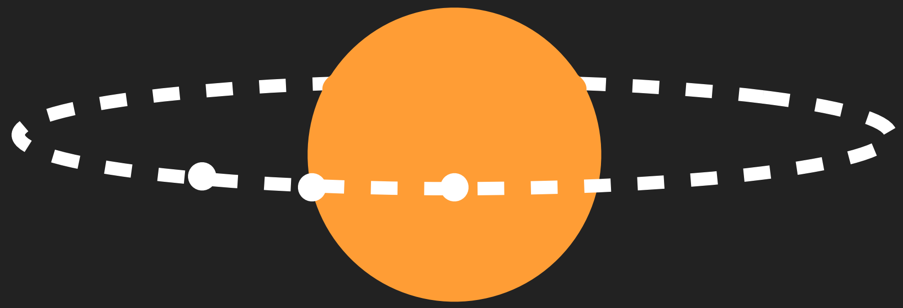


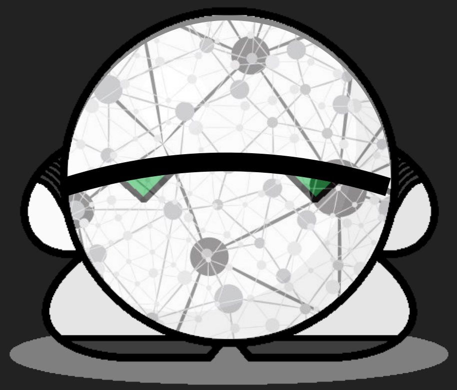


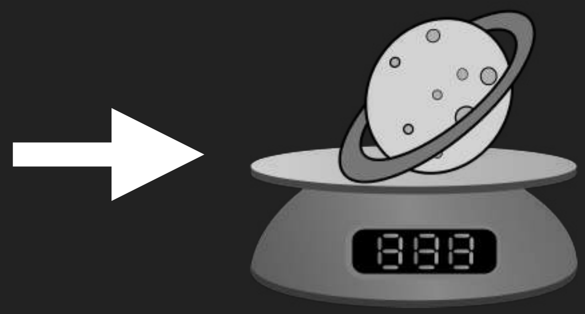


Test results! Transit planets

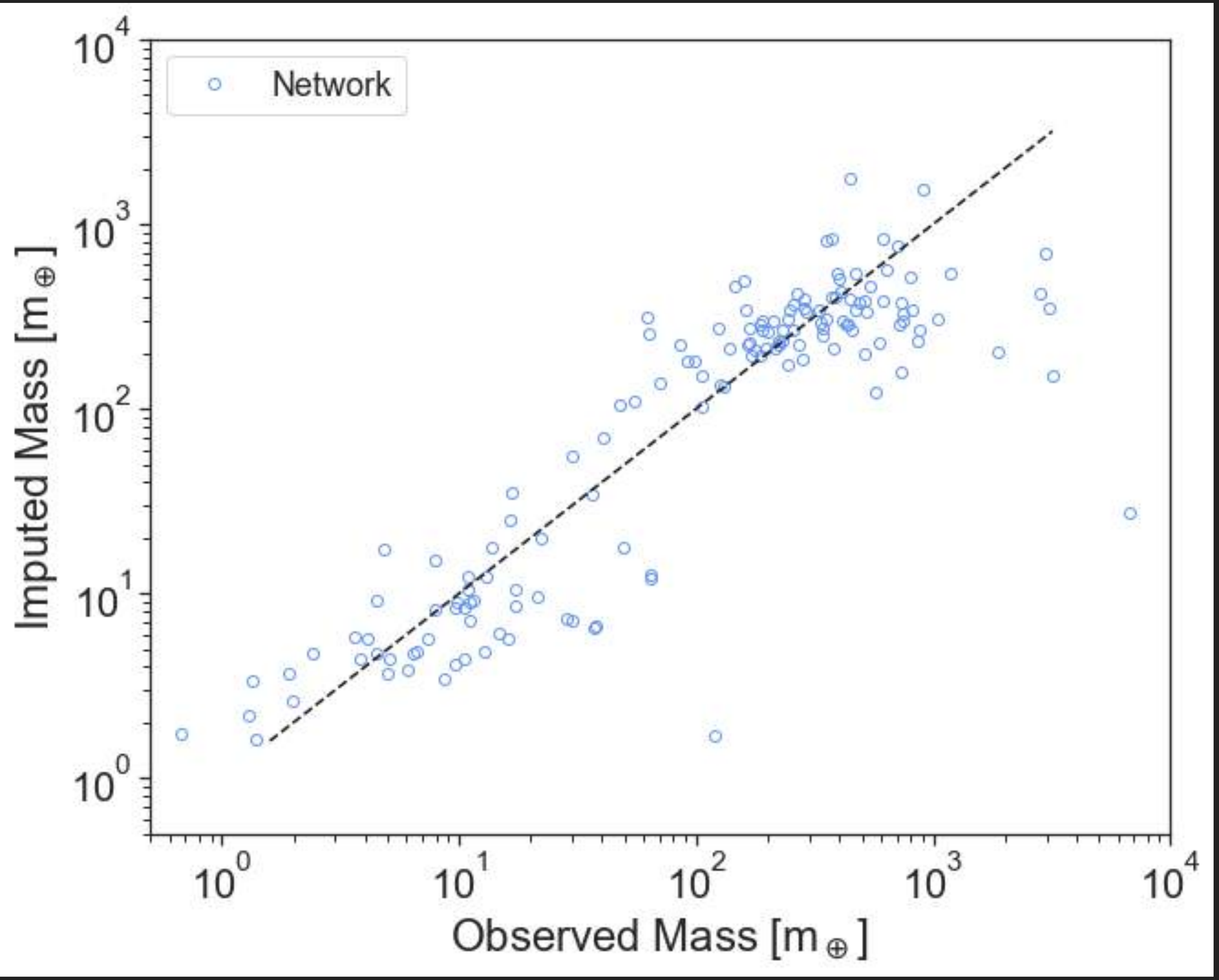
(pretend we only know radius and look at network generated masses)



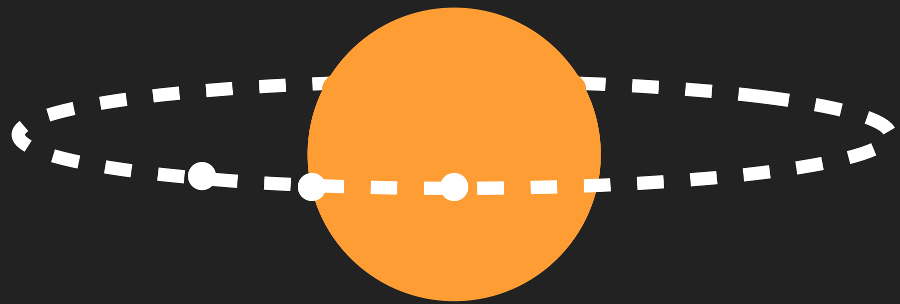


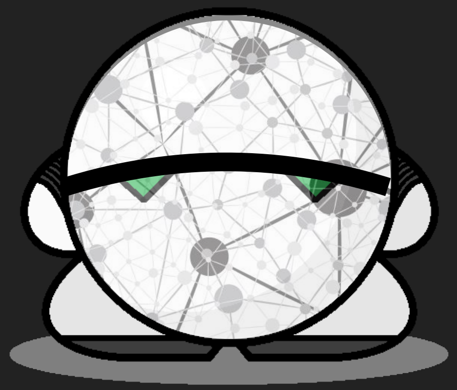


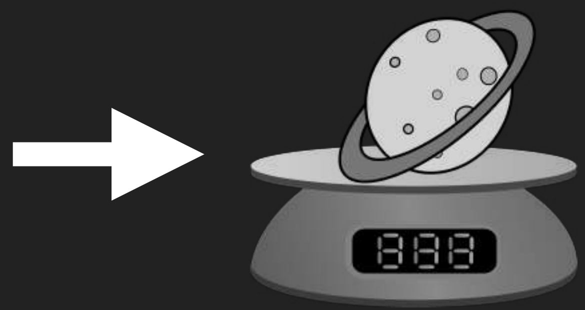
Test results! Transit planets



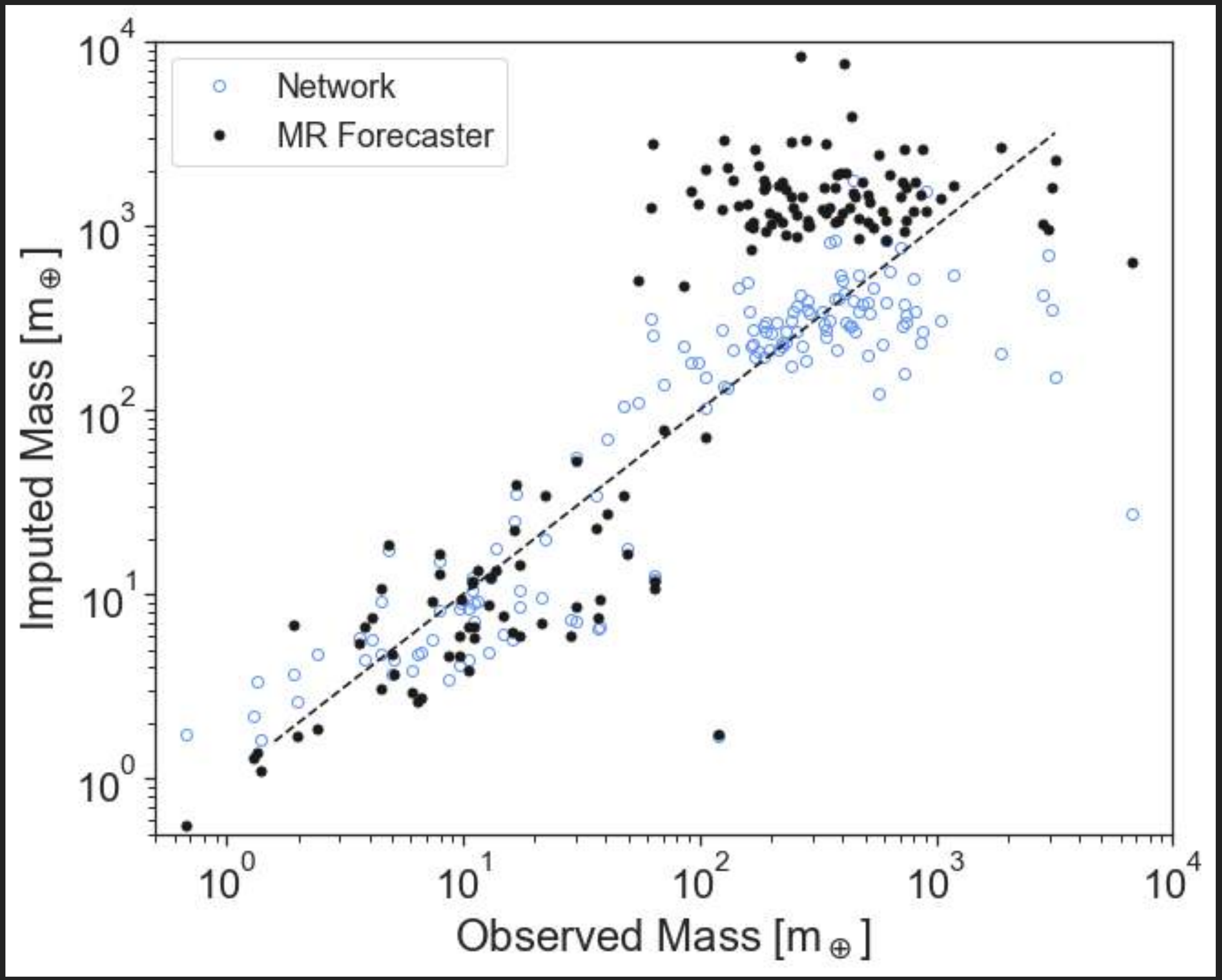
How does this compare with other methods?





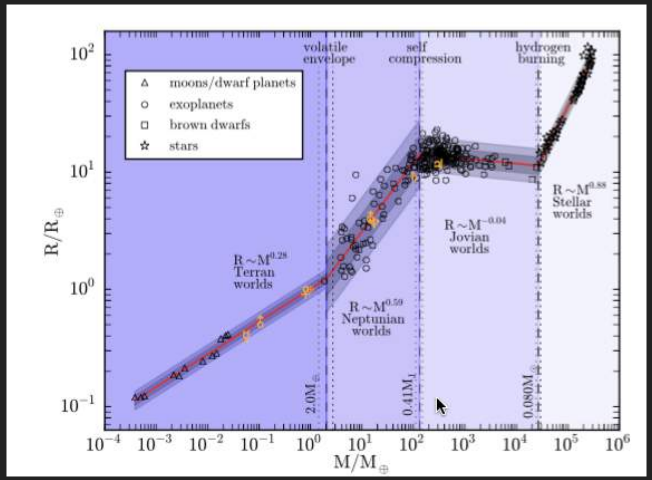


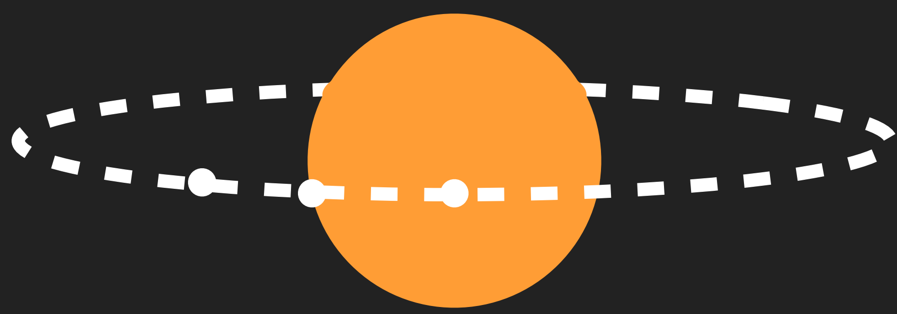
Test results! Transit planets

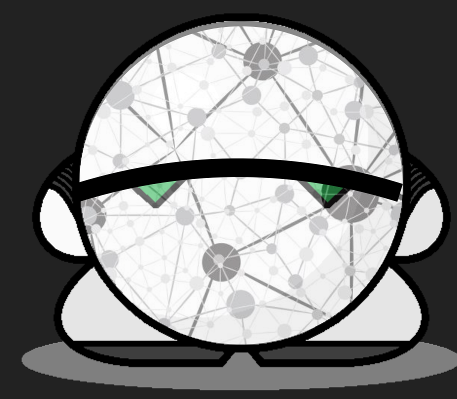


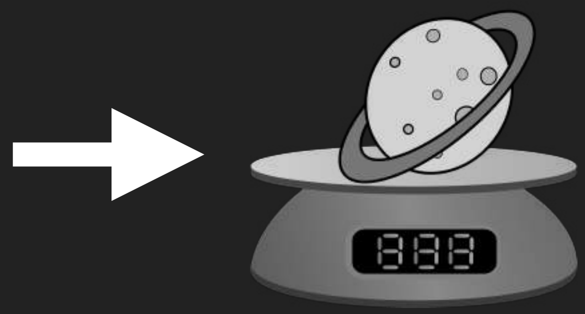
MR Forecaster

(Chen & Kipping, 2017)

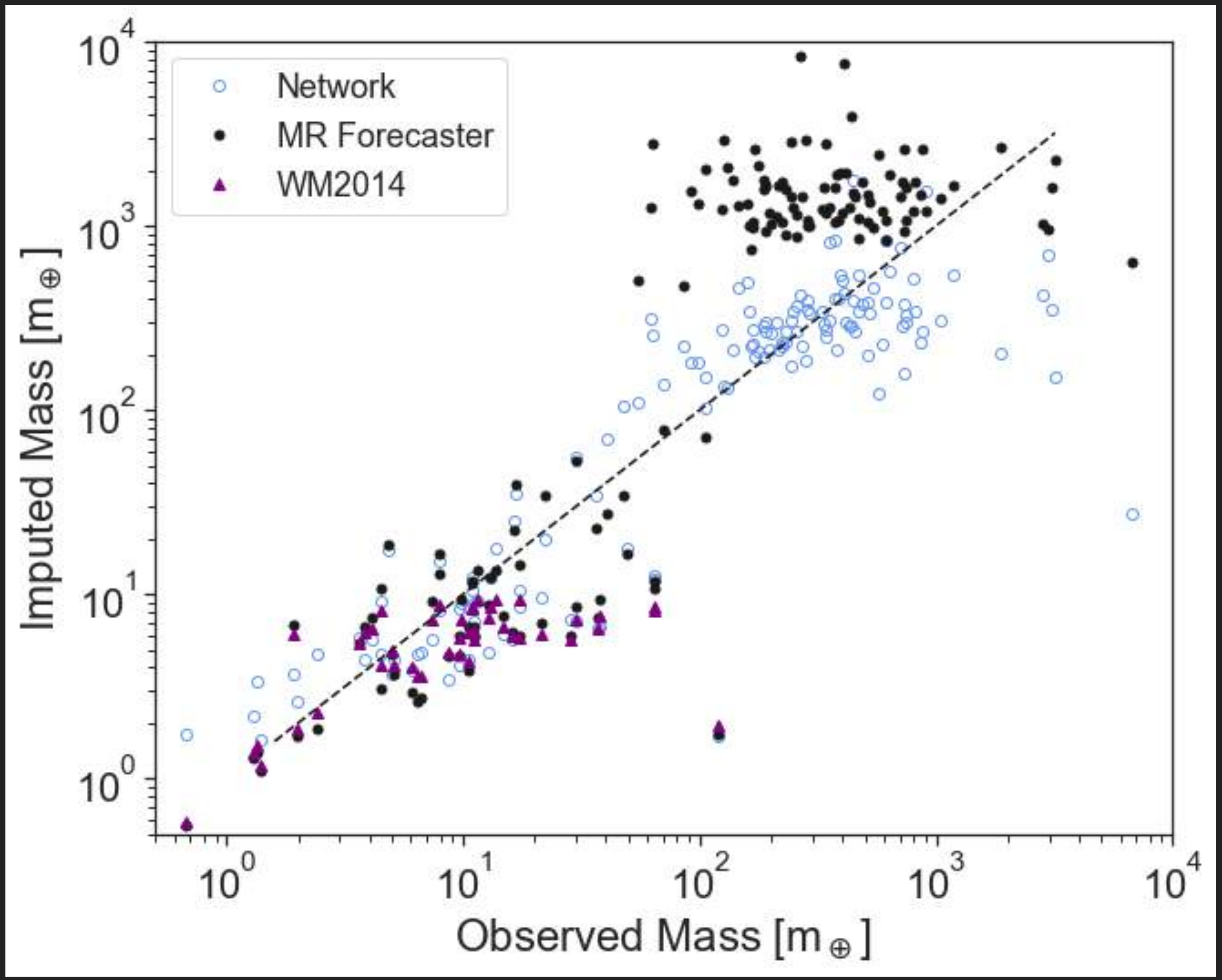






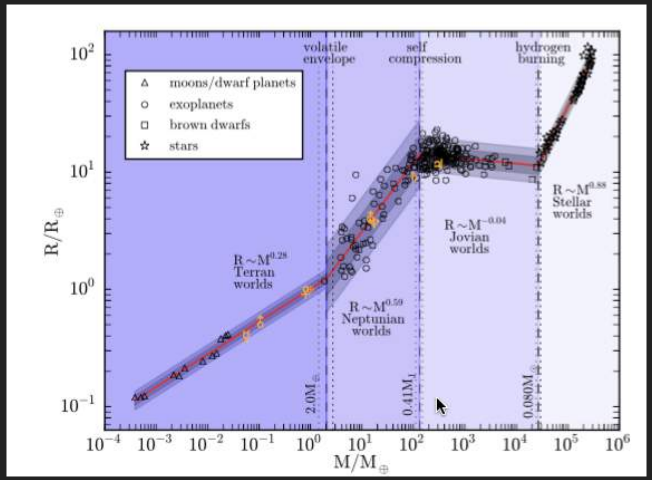


Test results! Transit planets



MR Forecaster

(Chen & Kipping, 2017)

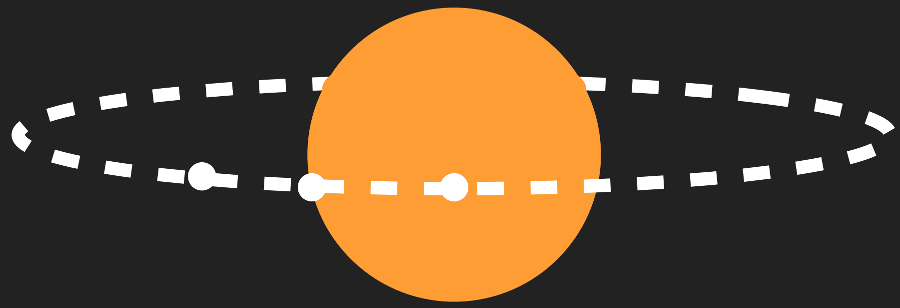


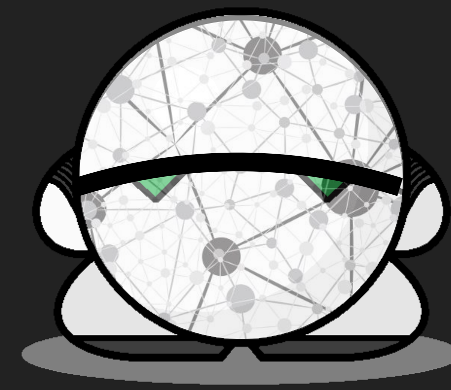
Weiss & Marcy, 2014

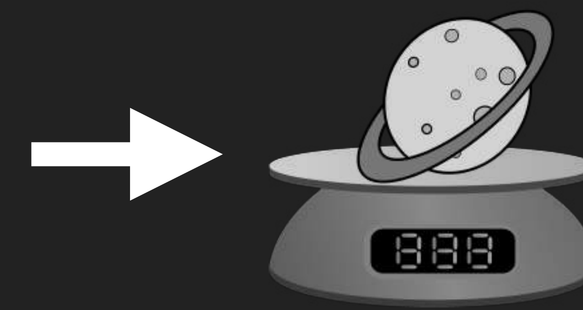
(Empirical < 4 🌍)

$R_P < 1.5 R_\oplus \qquad \rho_P = 2.43 + 3.39 \left(\frac{R_P}{R_\oplus} \right) \mathrm{gcm}^{-3}$

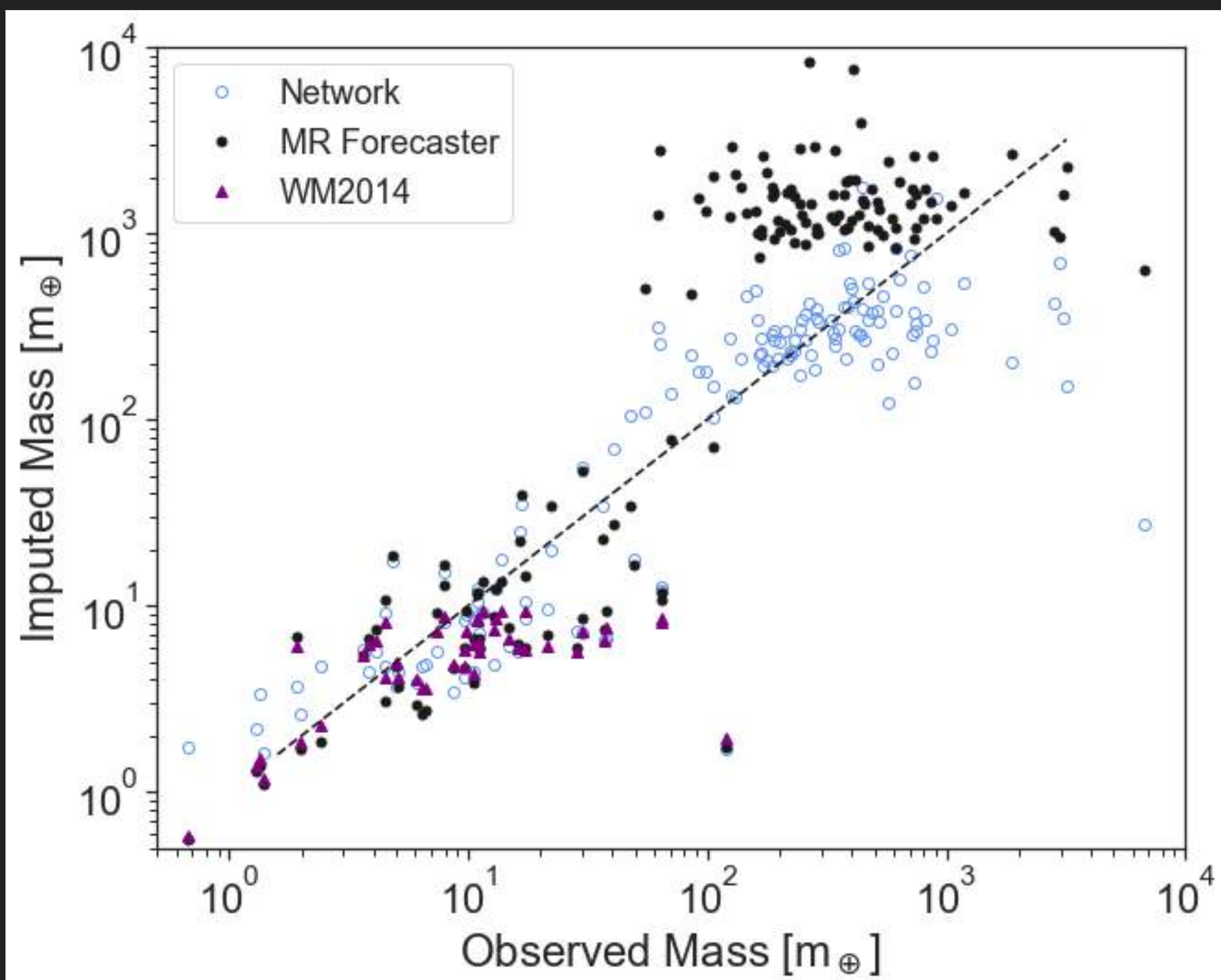
$1.5 \leq R_P / R_\oplus < 4 \qquad \frac{M_P}{M_\oplus} = 2.69 \left(\frac{R_P}{R_\oplus} \right)^{0.93}$







Test results! Transit planets



Errors:

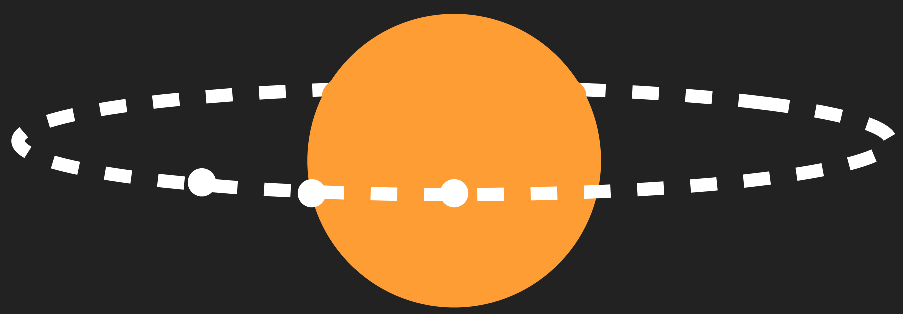
Network = 0.98

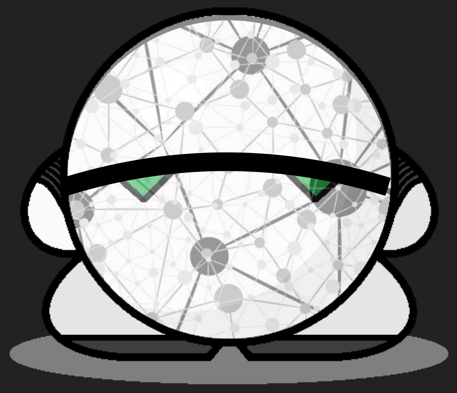
Forecaster = 1.6

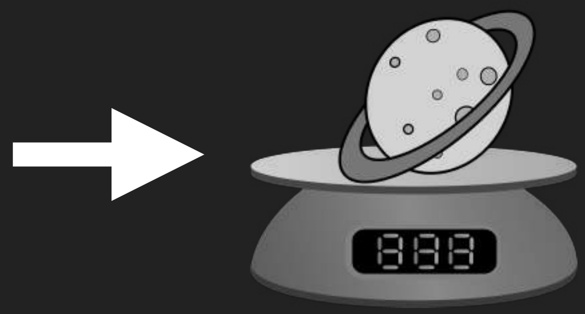
WM2014 (< 4 RE) = 1.02

On average, network finds a planet mass ~2.7 x true mass

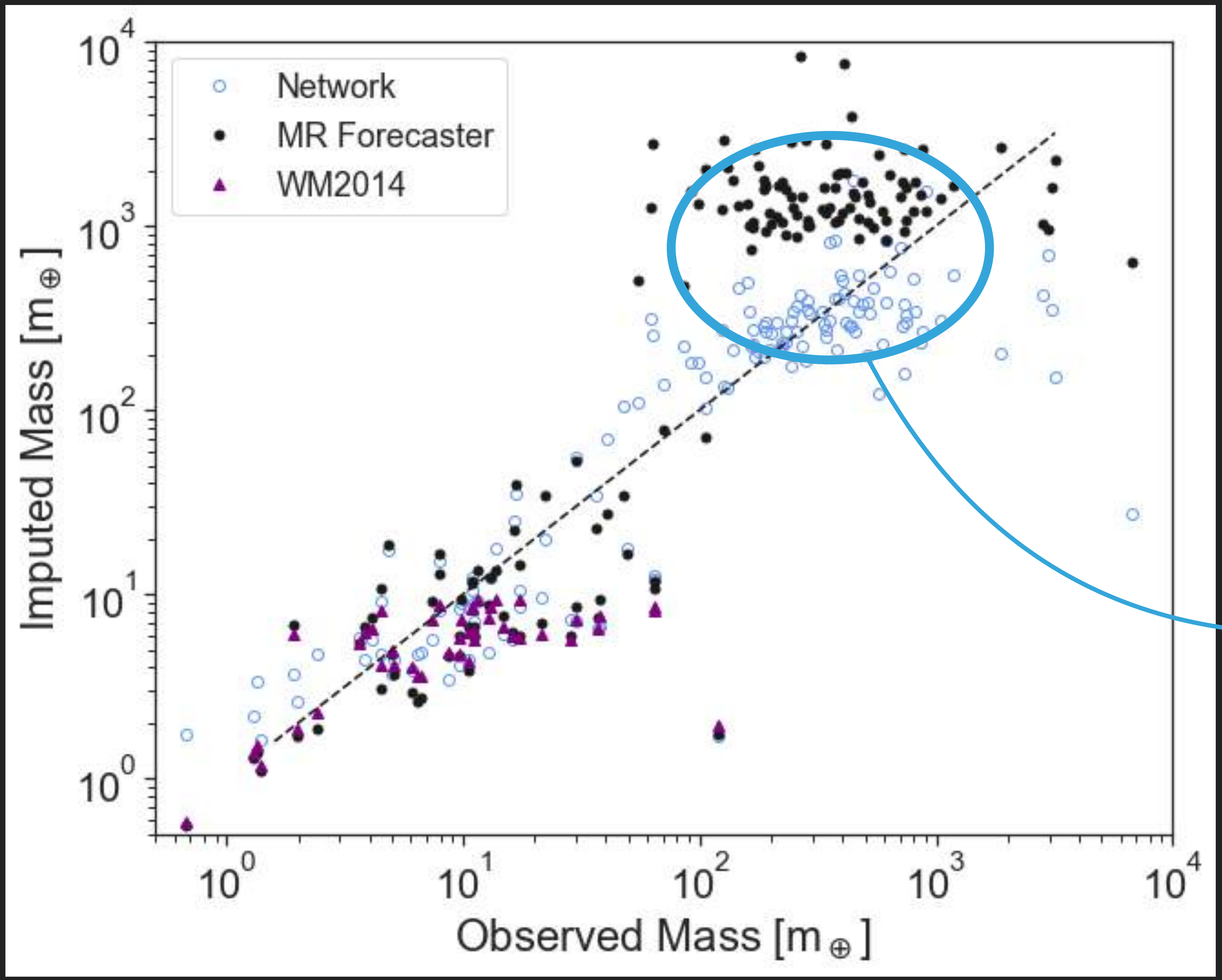
But why more scatter?





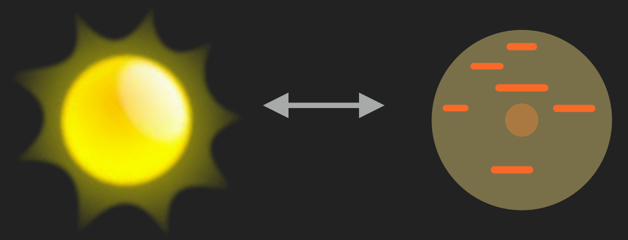


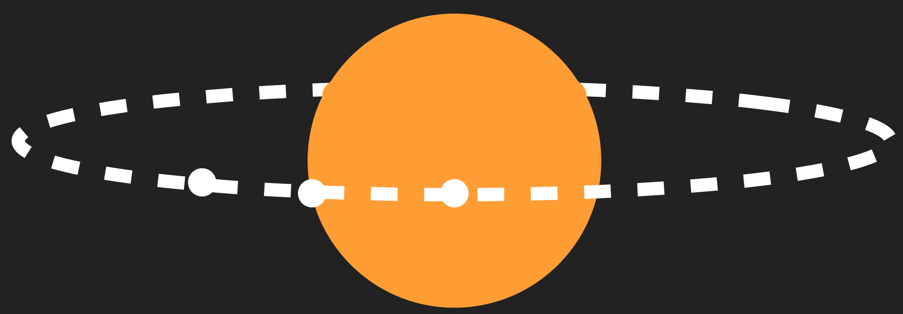
Test results! Transit planets

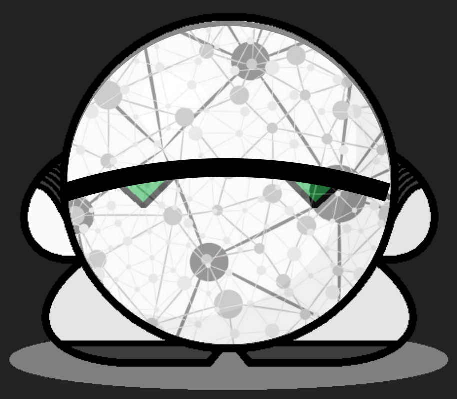


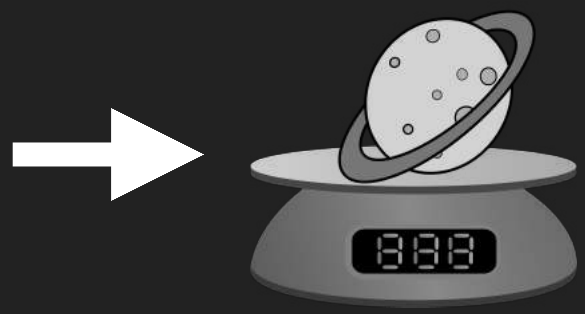
Higher error than RV as….

1. No minimum mass guide
2. Stellar degeneracy in radius

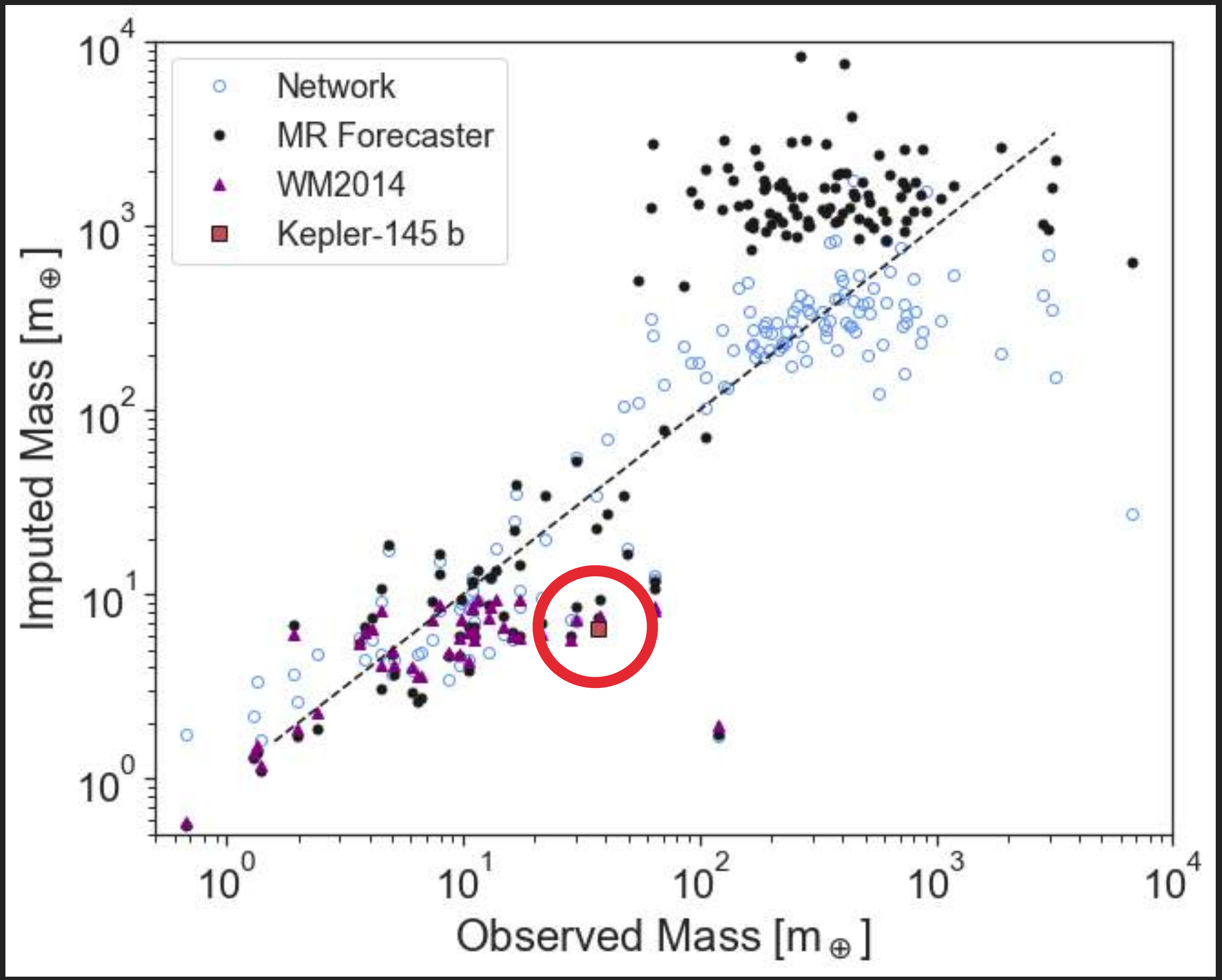








Test results! Transit planets

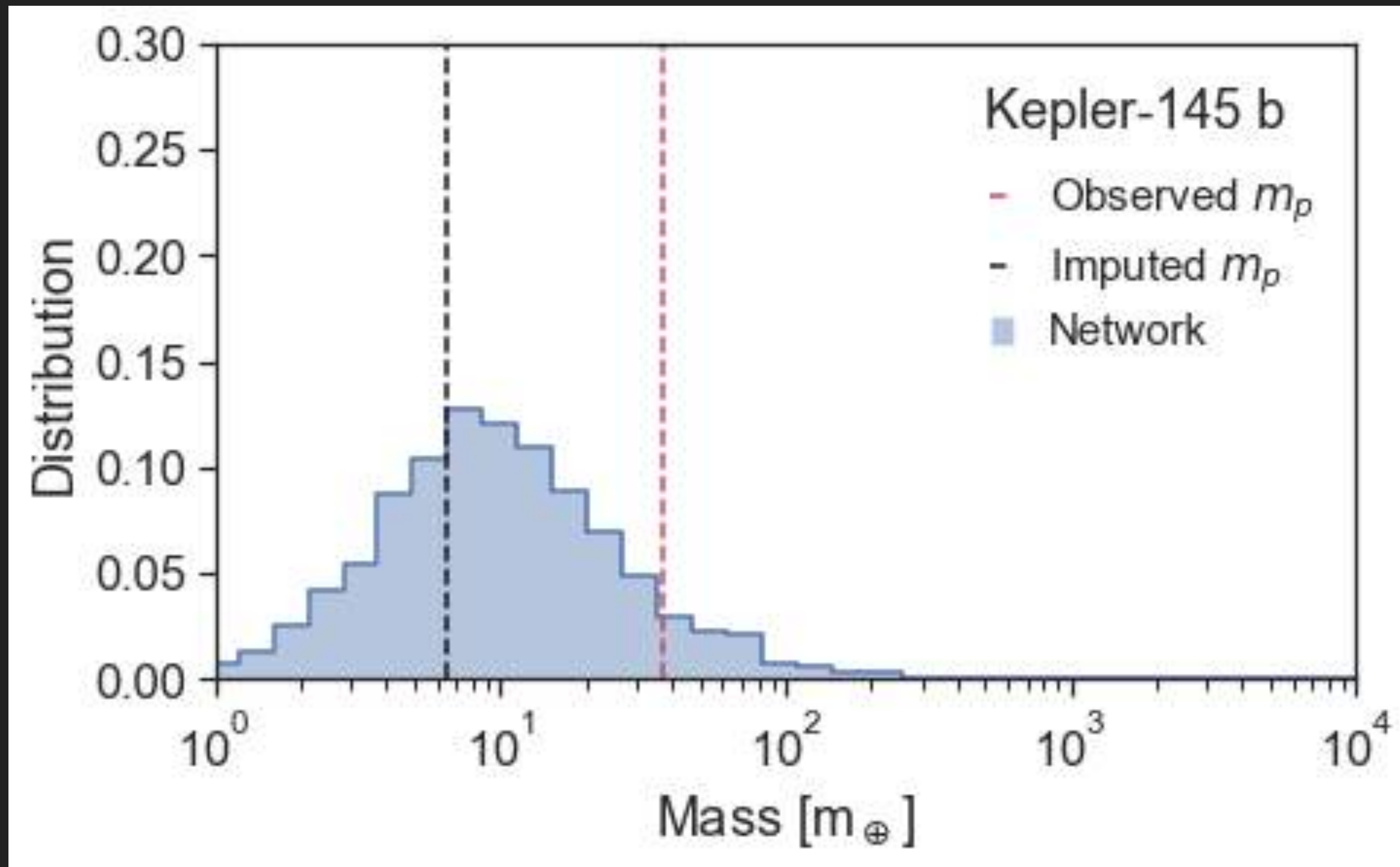


How about the bad planets?

Kepler-145 b has a high error

Why?!

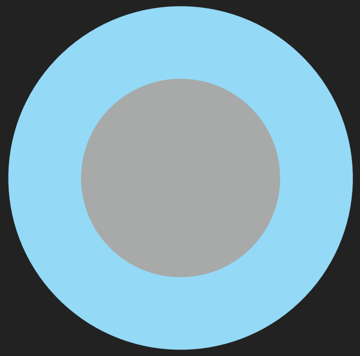
Bad Worlds



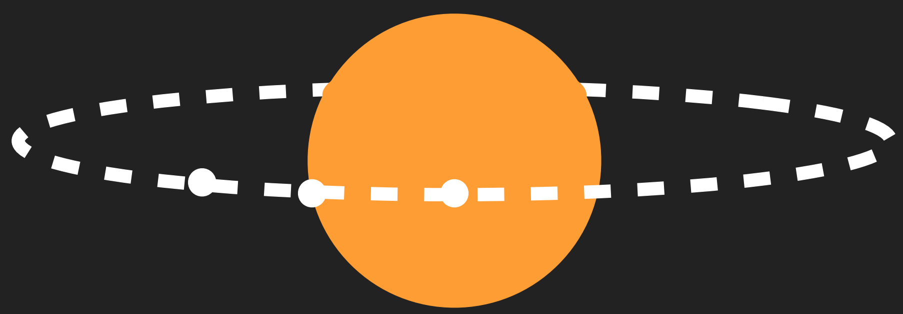
Unusually large rocky planet

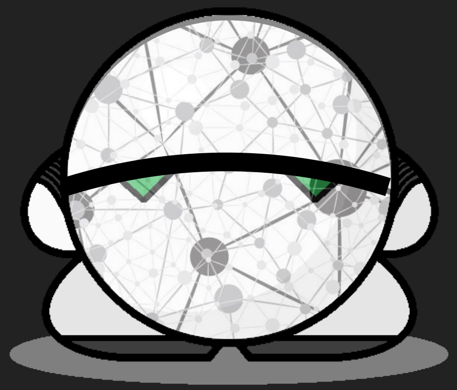
$M = 37.1 M_\oplus \quad R = 2.65 R_\oplus$

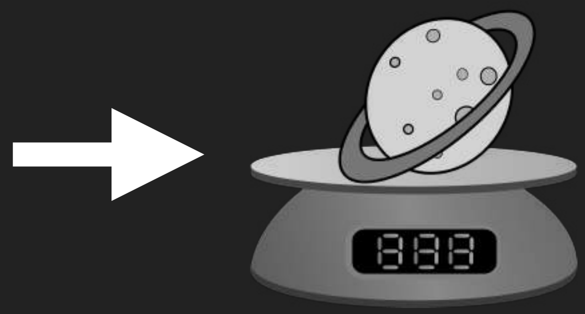
$\rho = 11.0\,\mathrm{g/cm^3}$



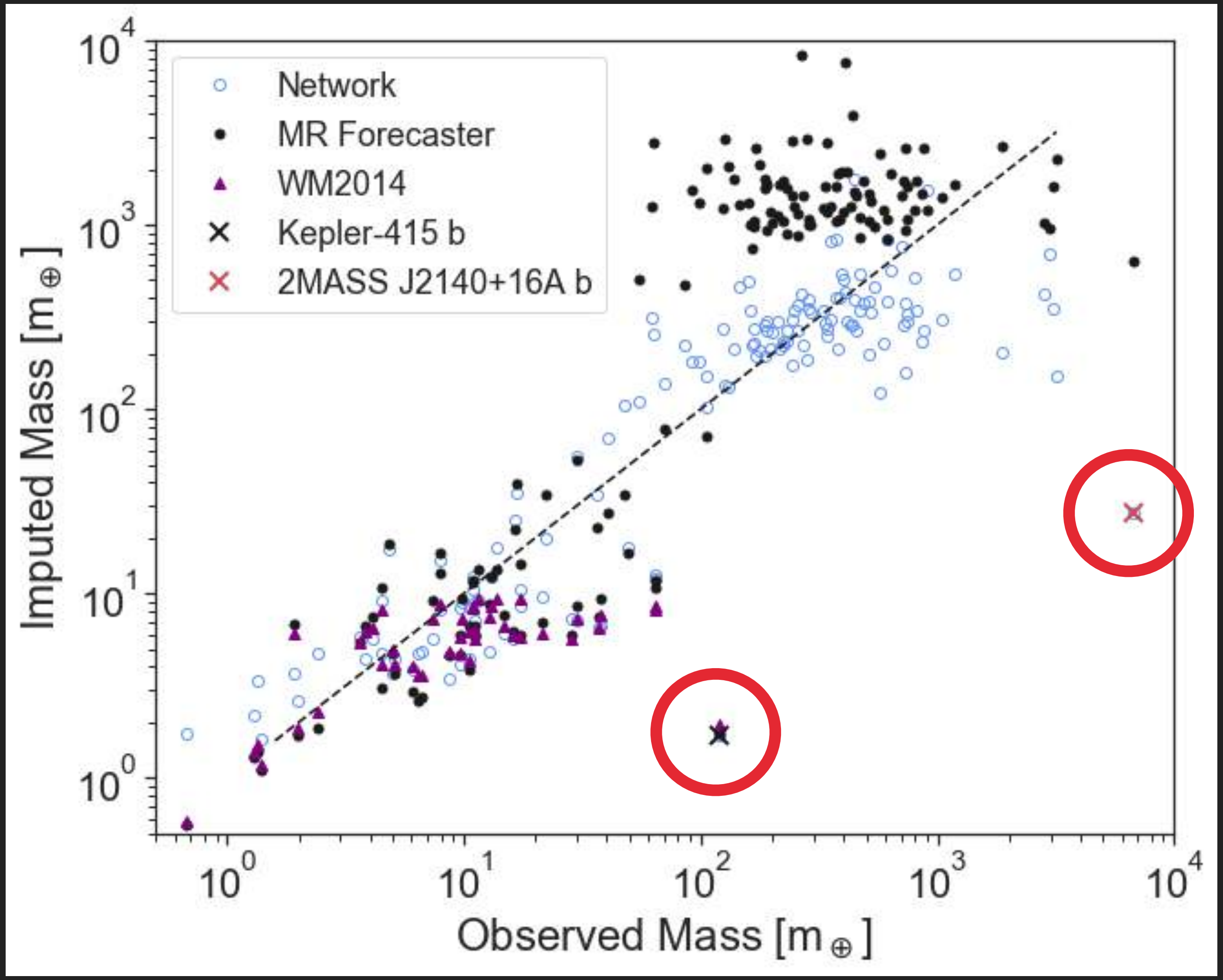
Network thinks this planet should have a thick atmosphere (and lower mass)







Test results! Transit planets

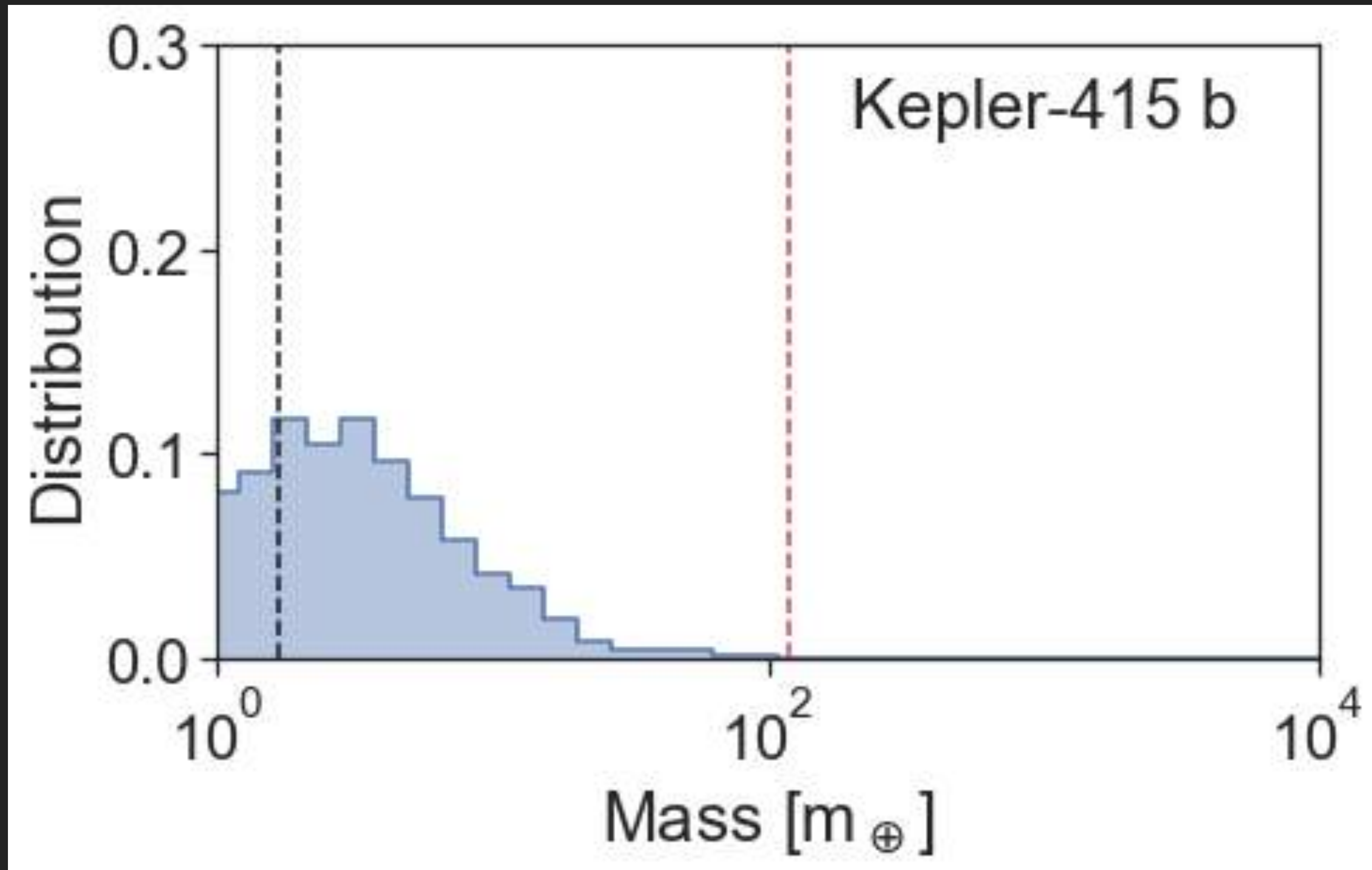


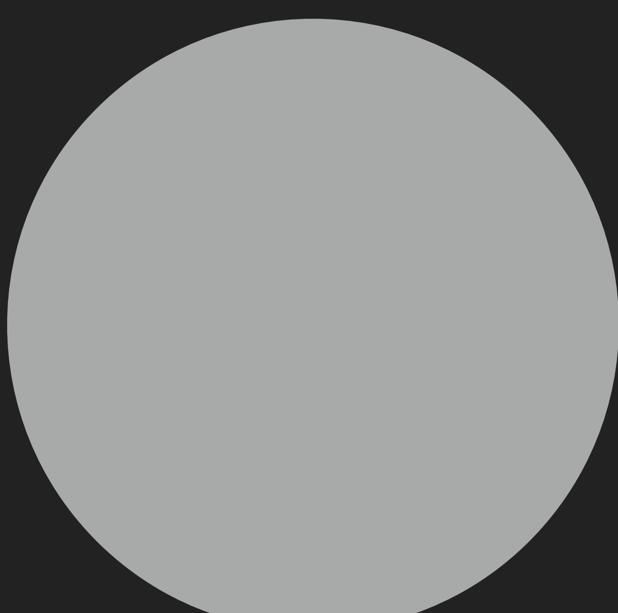
How about the REALLY bad planets?

Kepler-415b

2MASS J2140+16A b

Really Bad Worlds



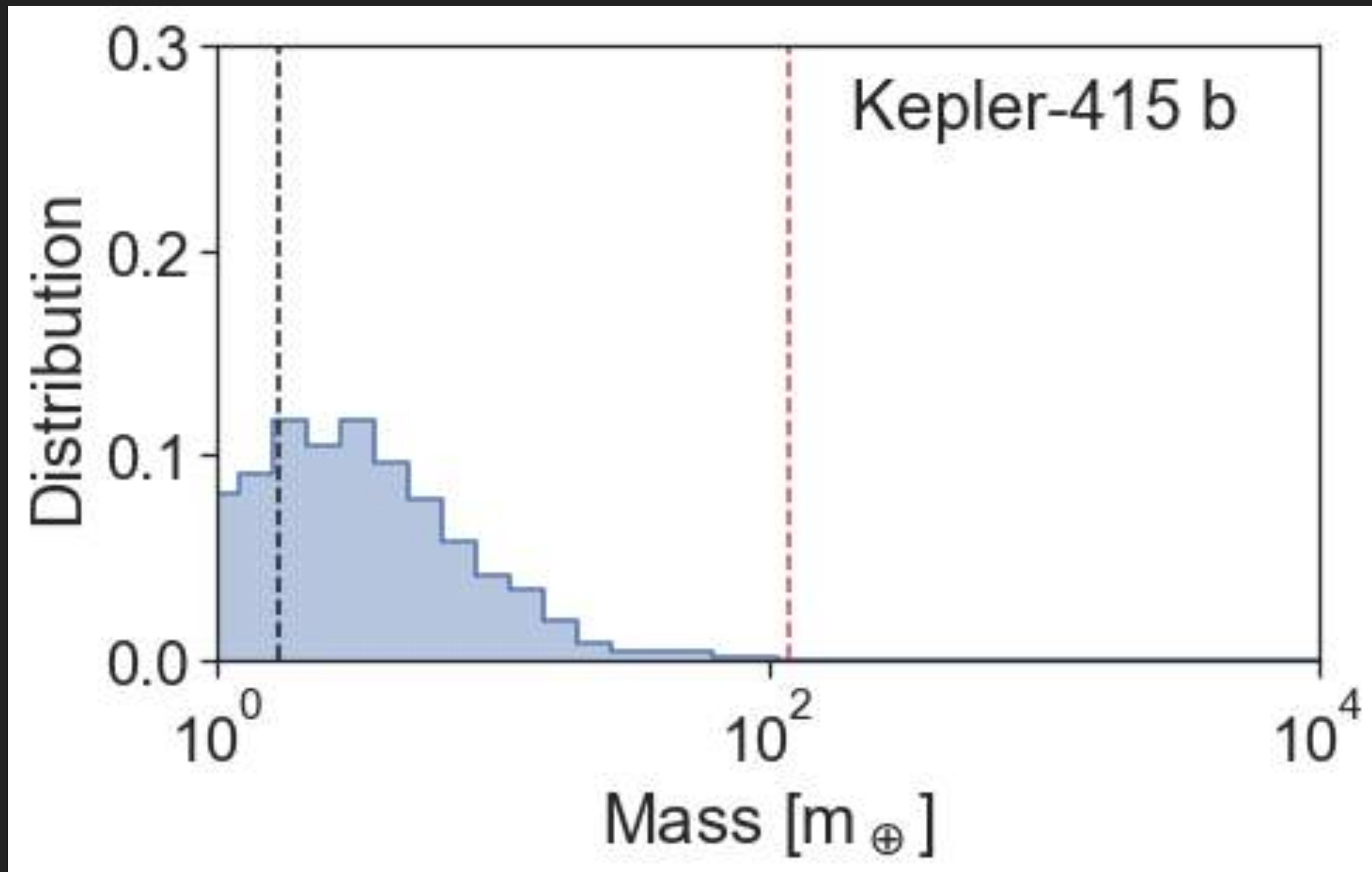


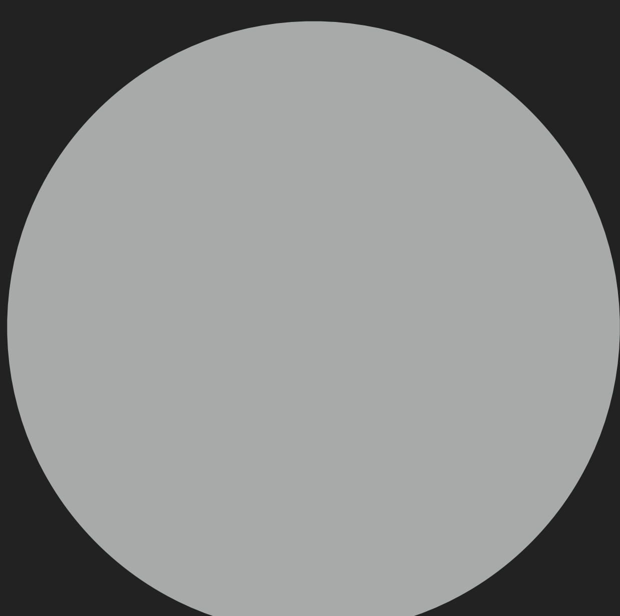
$$M = 120\,M_\oplus$$

$$R = 1.2\,R_\oplus$$

$$\rho = 373.1\ \mathrm{g/cm^3}$$ **!!!**

Really Bad Worlds

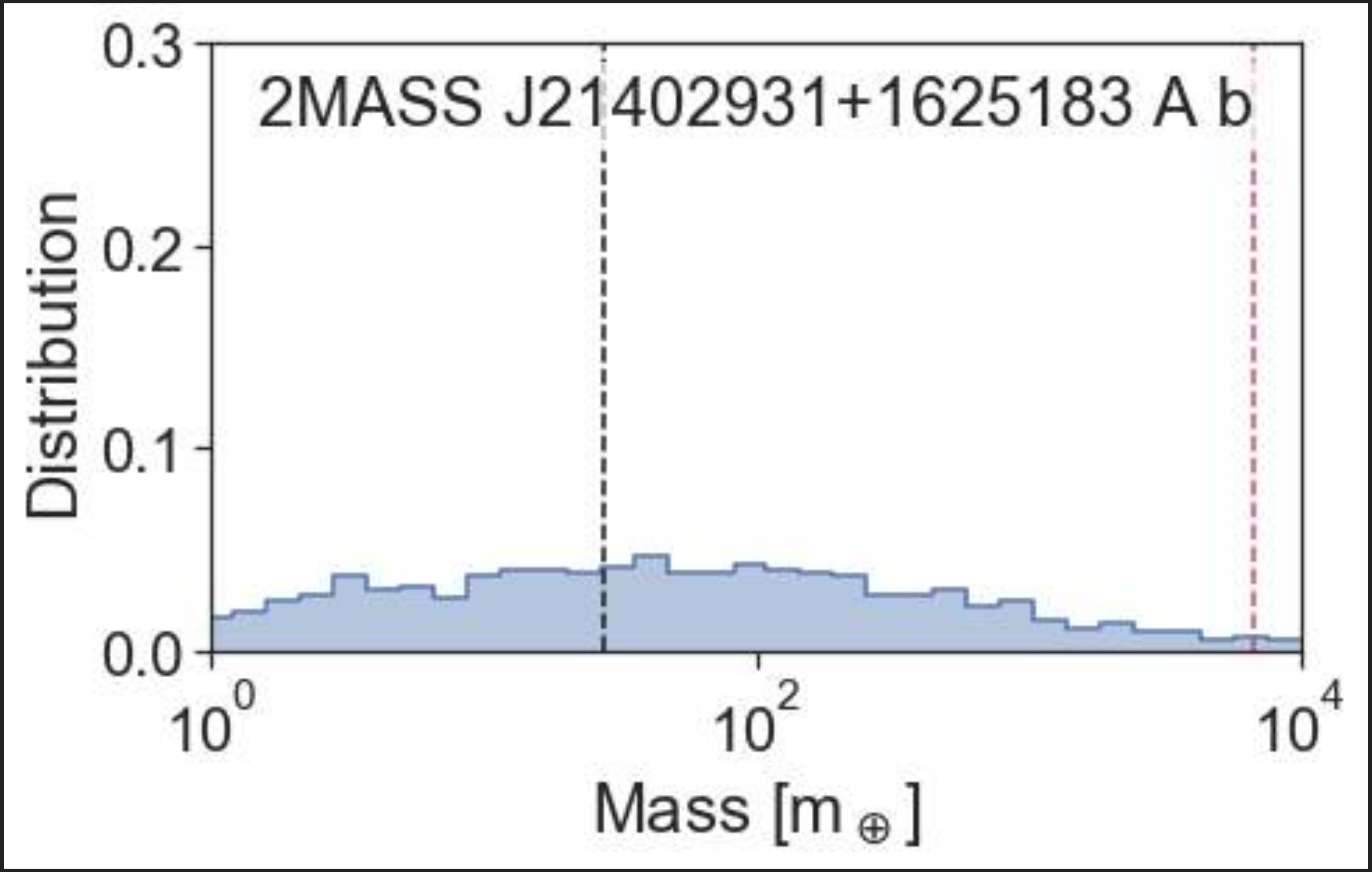




$$M = 120^{+102.1}_{-87.4}\, M_\oplus$$

Network estimate: $M = 1.7\, M_\oplus$

Really Bad Worlds

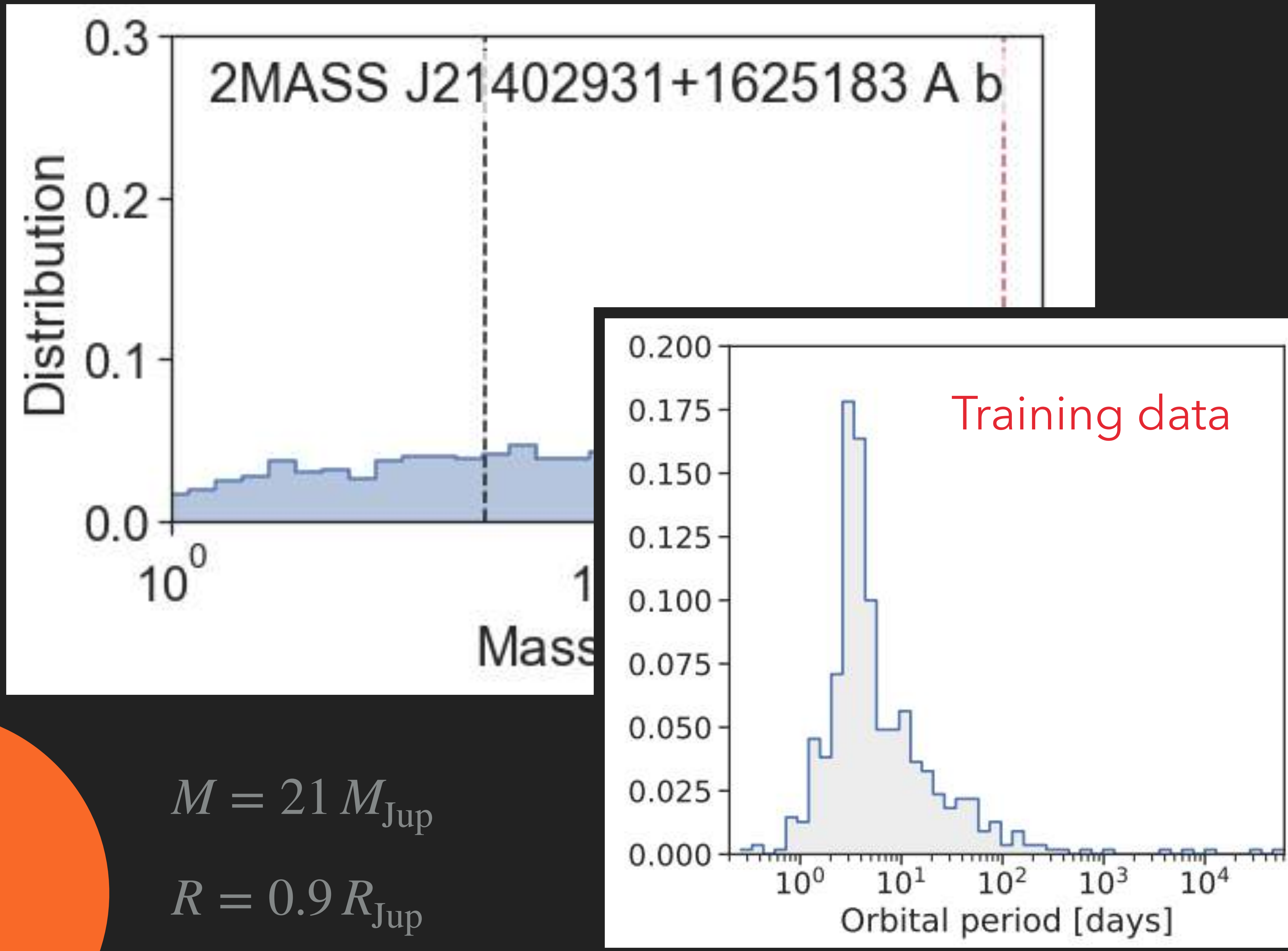


$M = 21\,M_{\rm Jup}$ ← Possible brown dwarf

$R = 0.9\,R_{\rm Jup}$

$P = 20$ years ← Very little data here!

Really Bad Worlds



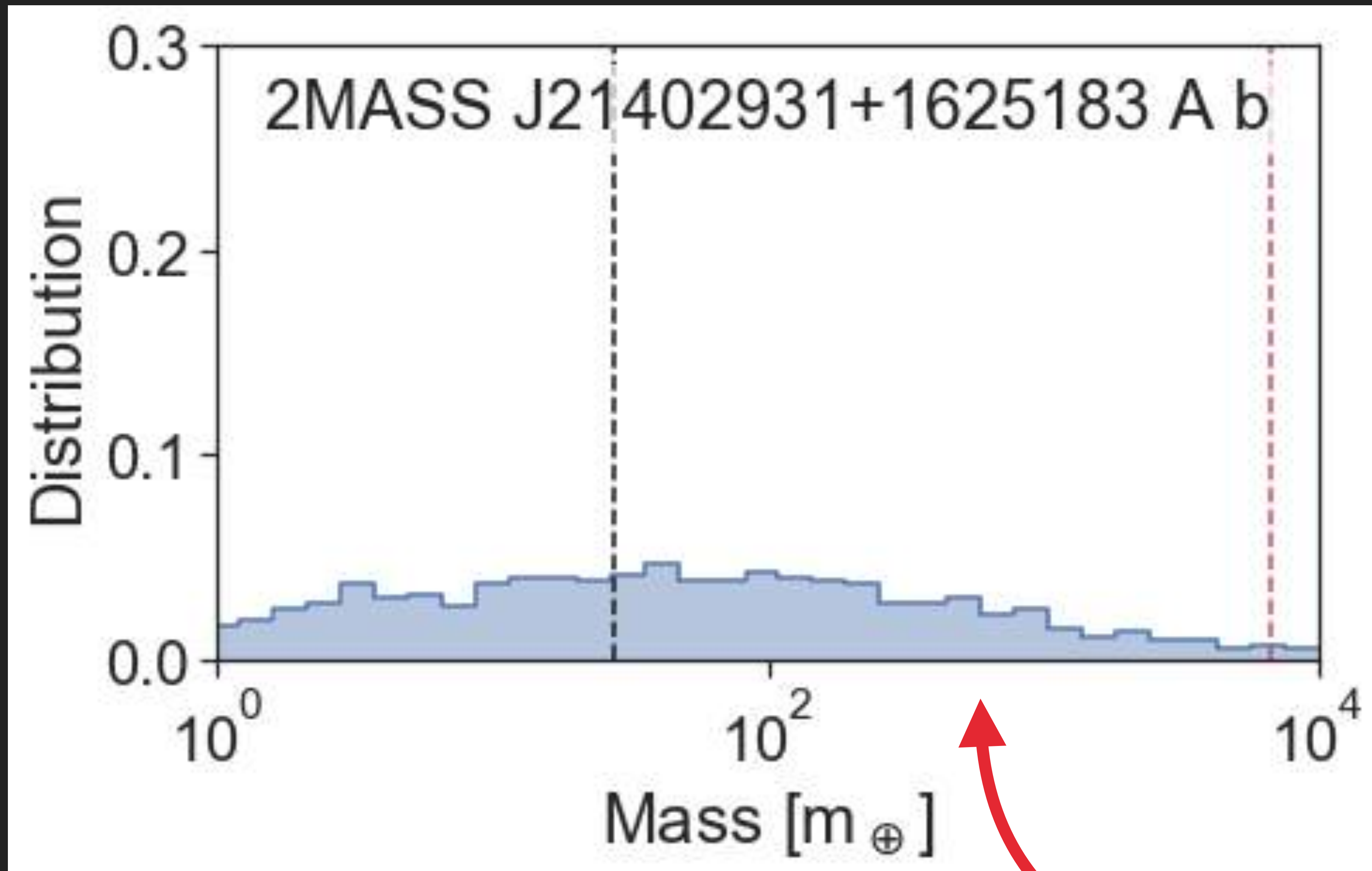
$M = 21\, M_{\rm Jup}$

$R = 0.9\, R_{\rm Jup}$

$P = 20\,$ years

Very little data here!

Really Bad Worlds

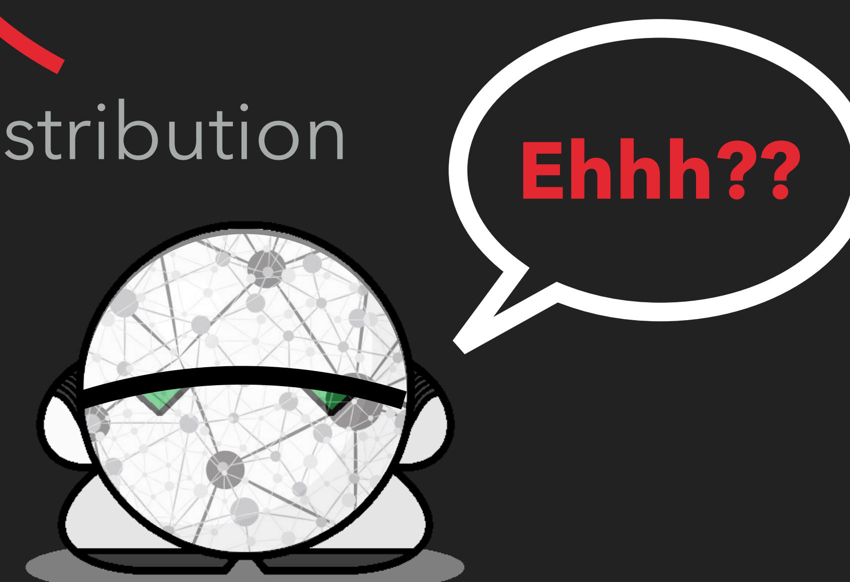


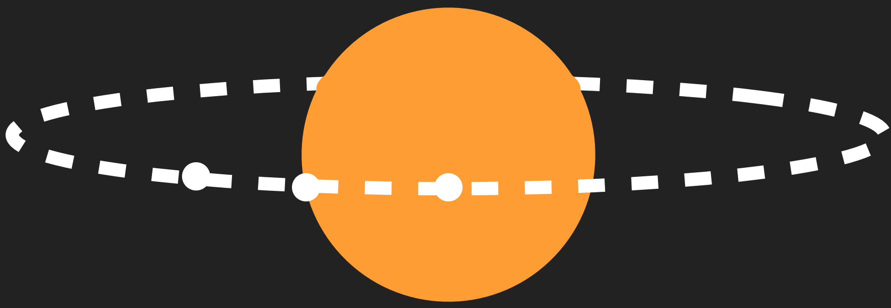
Flat distribution

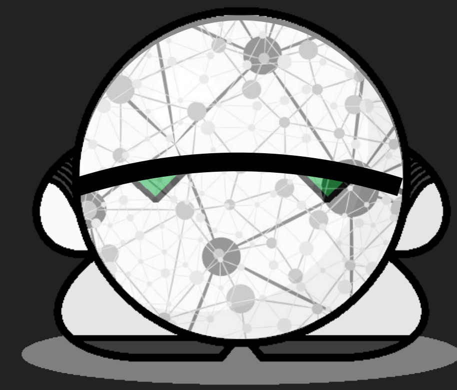
$M = 21\,M_{\mathrm{Jup}}$

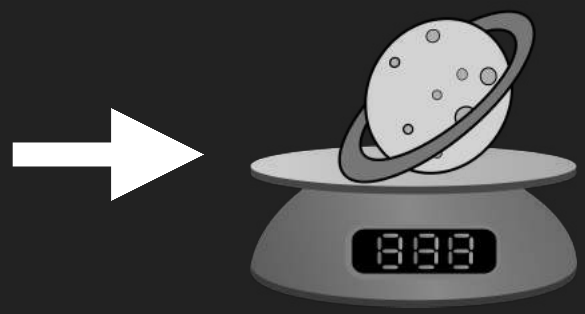
$R = 0.9\,R_{\mathrm{Jup}}$

$P = 20$ years

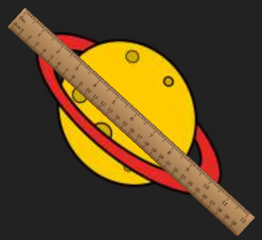


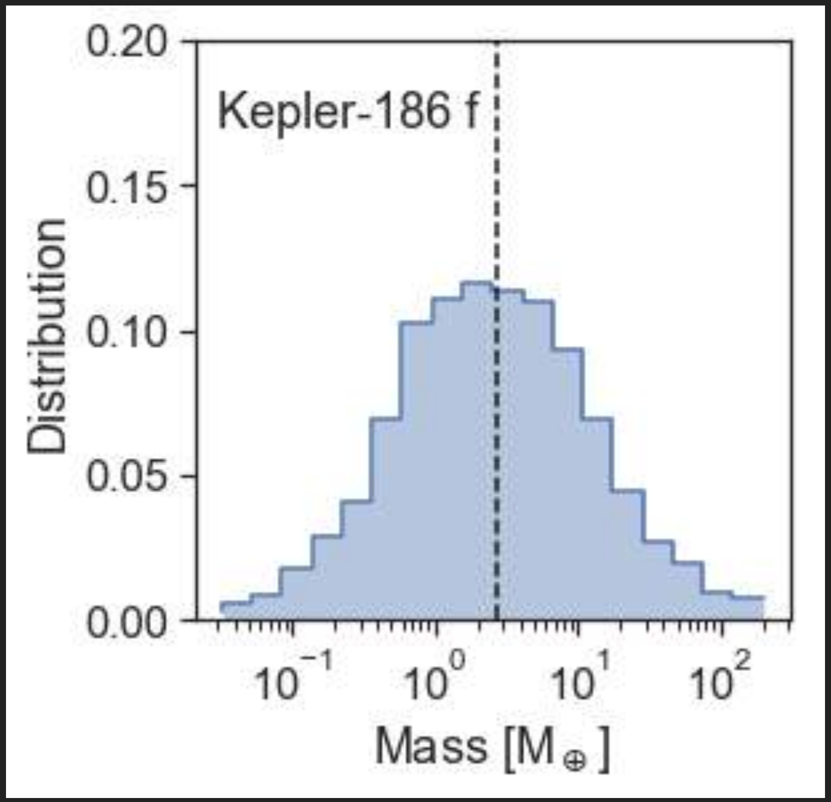




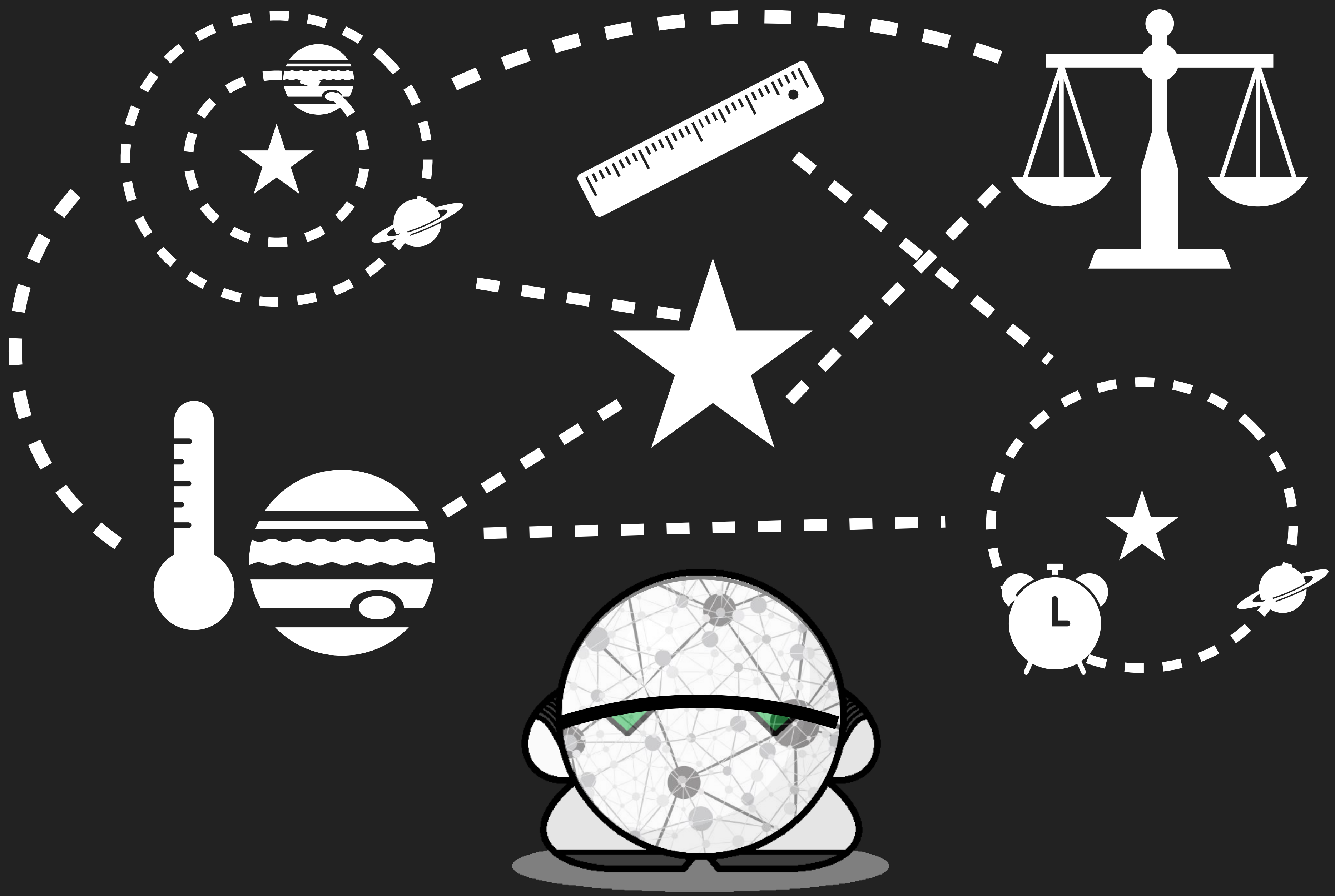


Kepler-186f

 ~ 1.1 

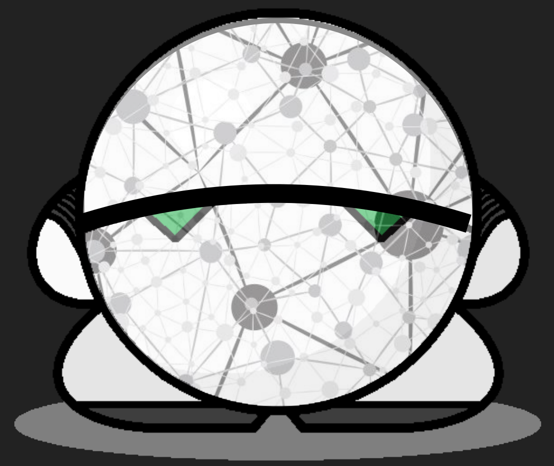


 $2.7^{+11.1}_{-2.2}$ 



Neural networks can identify trends between planet properties

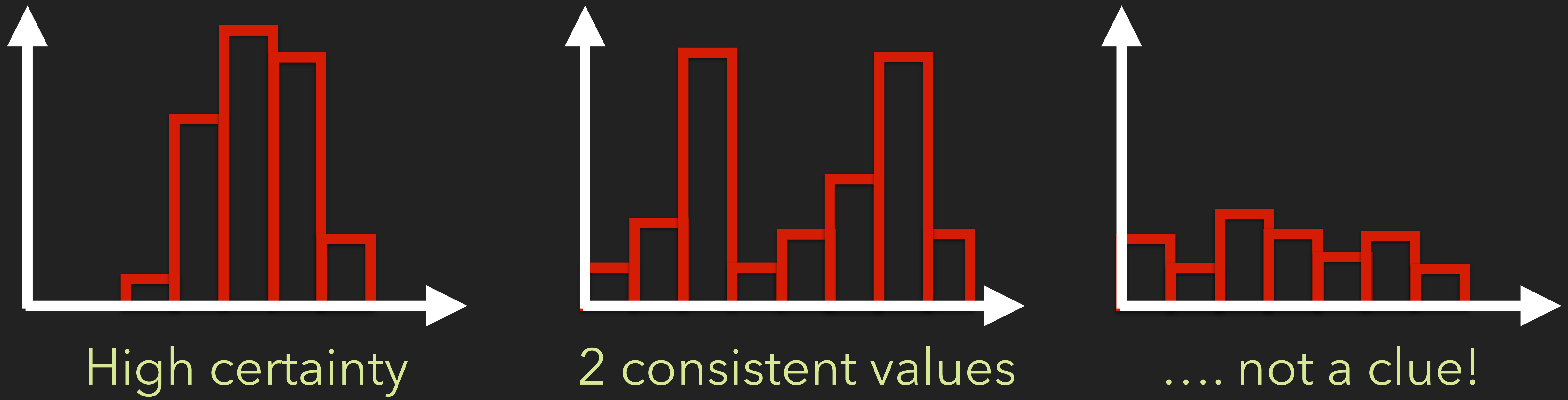
… to interpolate between known data and estimate missing values

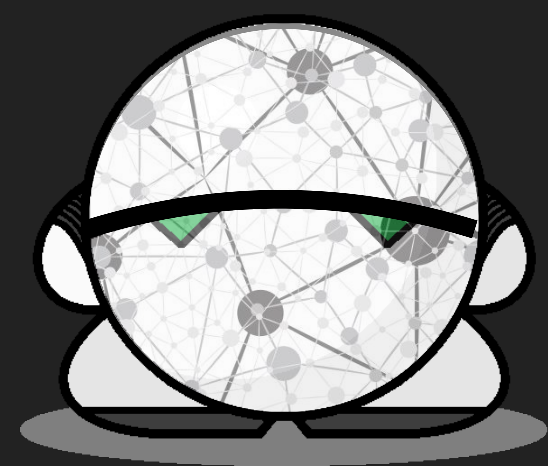


Neural networks can identify trends between planet properties

… to interpolate between known data and estimate missing values

Best performance in densely populated parameter space



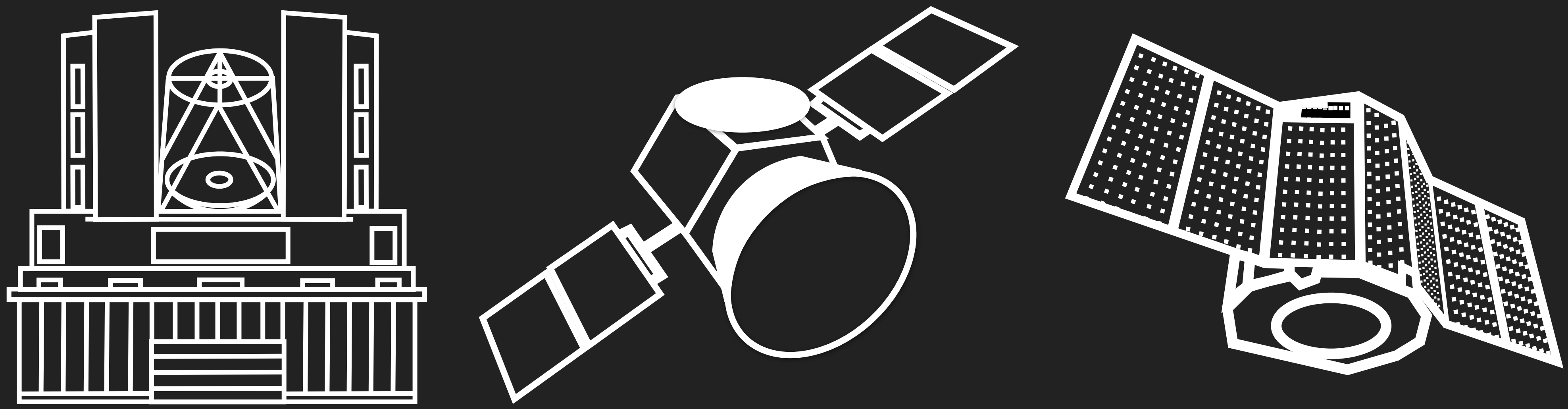


Neural networks can identify trends between planet properties

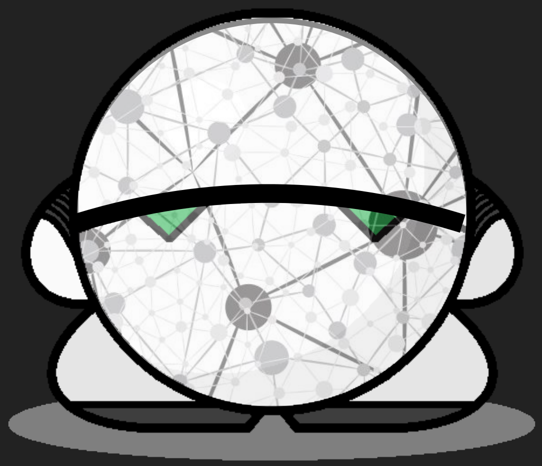
… to interpolate between known data and estimate missing values

Best performance in densely populated parameter space

Distribution contains important information.



All new data will improve the method



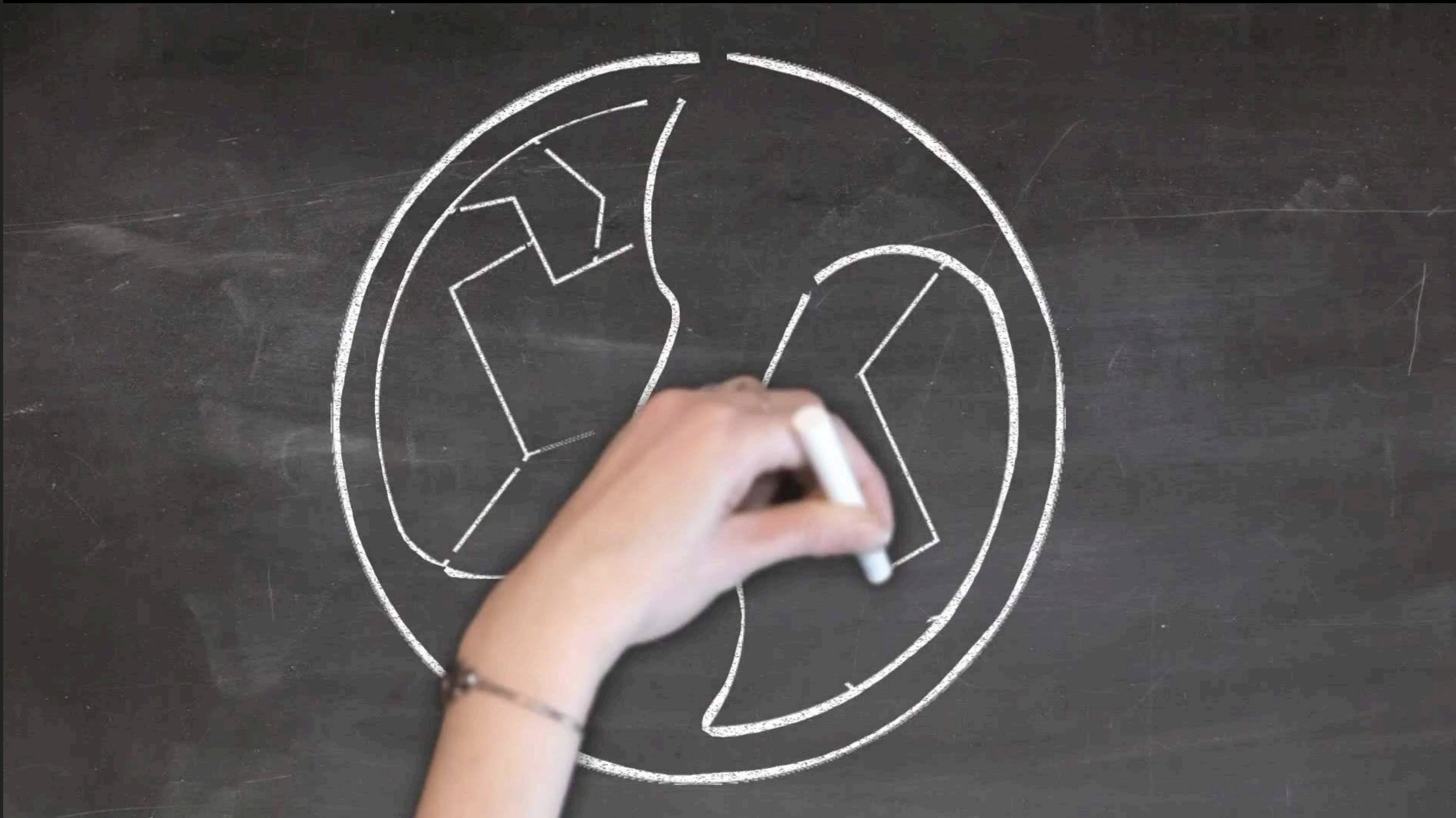
Neural networks can identify trends between planet properties

… to interpolate between known data and estimate missing values

Best performance in densely populated parameter space

Distribution contains important information.

Outreach: https://www.youtube.com/watch?v=cQygpmYwKw4



... or a world largely composed of ices or ocean.