

# Towards Better Planet Occurrence Rates from Kepler and K2

Andrew Vanderburg  
NASA Sagan Fellow  
The University of Texas at Austin

Sagan/Michelson Fellows Symposium  
November 9, 2017

# Collaborators



**Andy Mayo**

Harvard undergrad

—> Copenhagen Univ. Fulbright

—> UC Berkeley grad (Fall 2018)



**Chris Shallue**

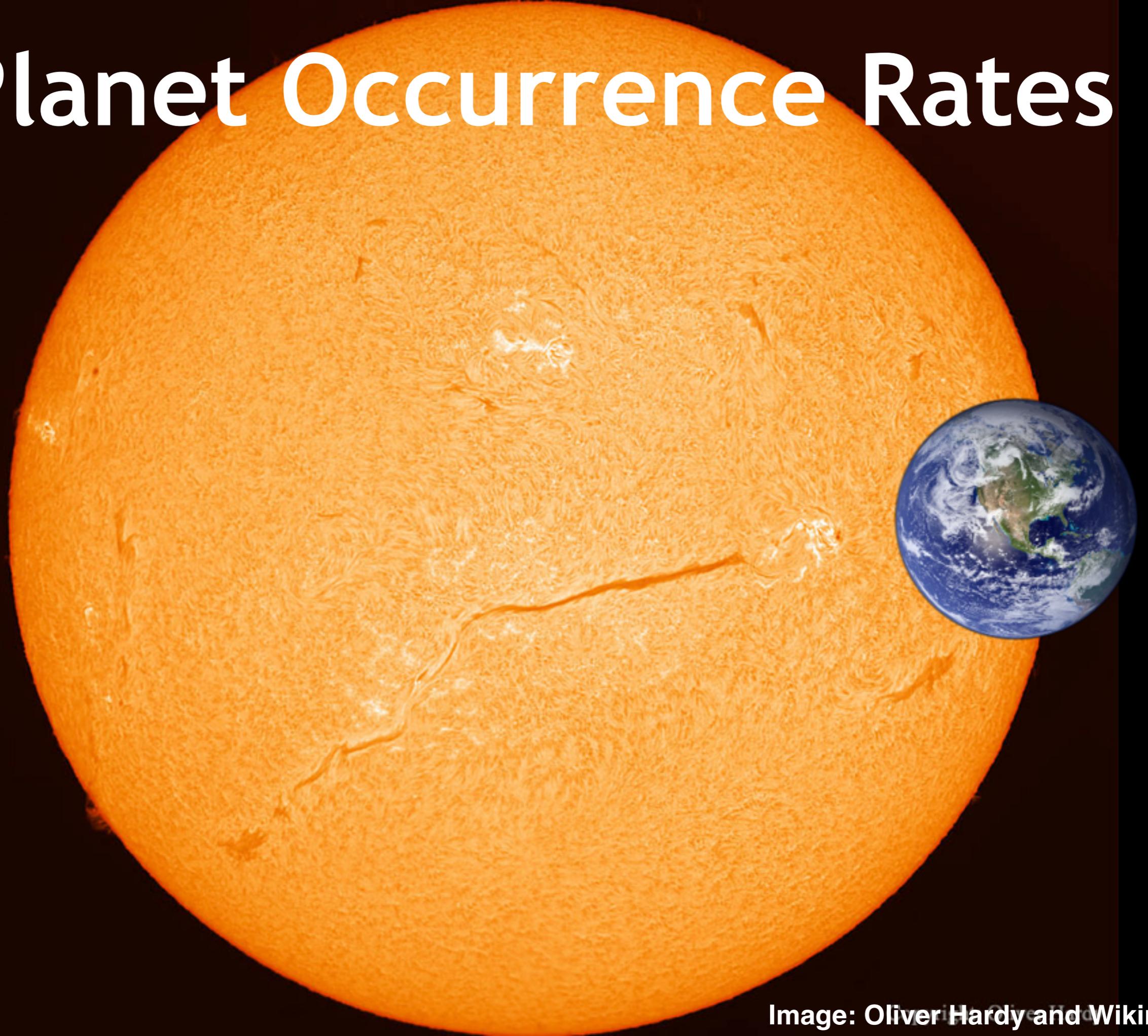
Google Brain

# Outline

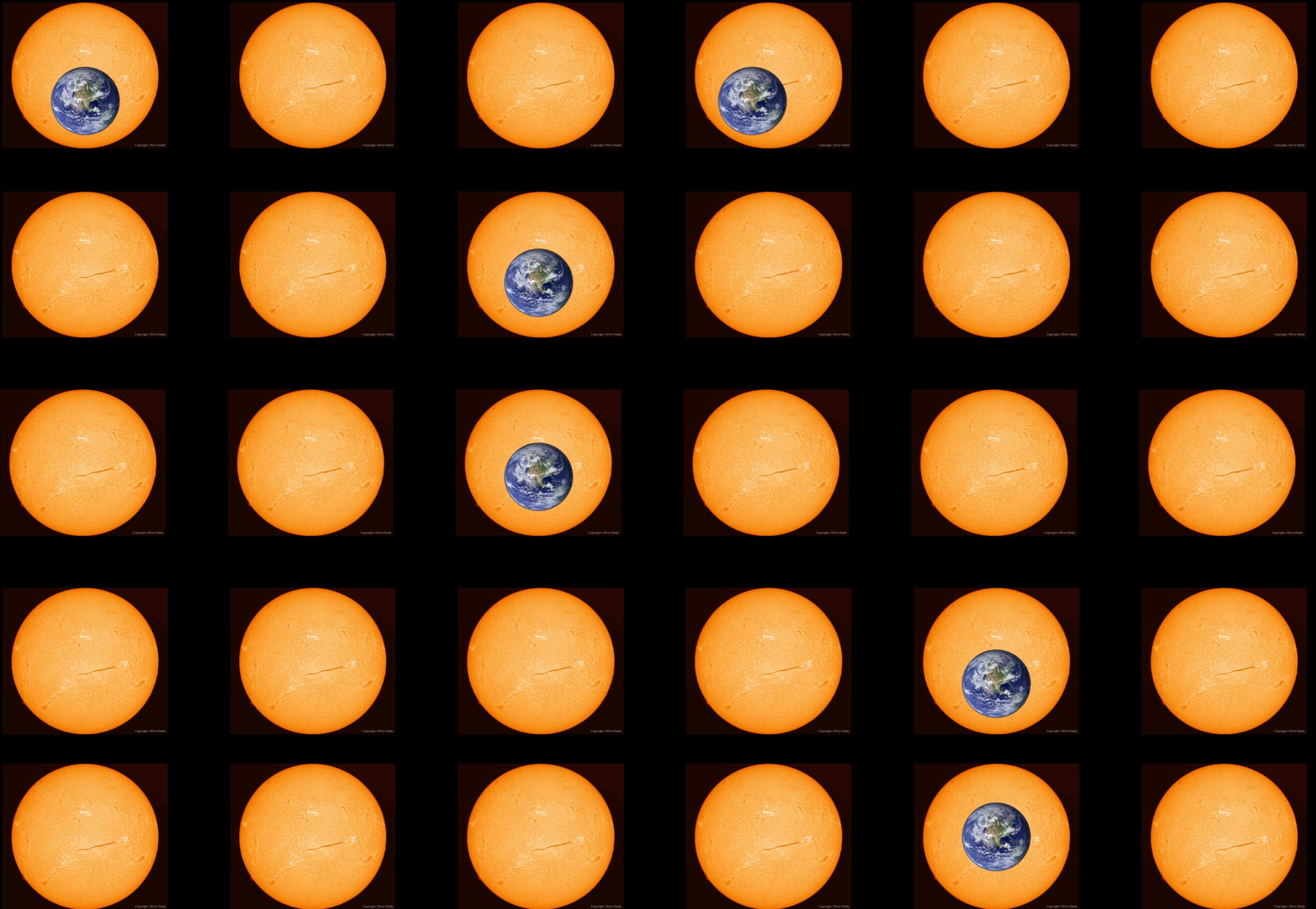
- Planet occurrence rates and where we stand now
- Neural networks and how we can use them to identify planets
- Spectroscopy of K2 candidates to measure the planet radius distribution



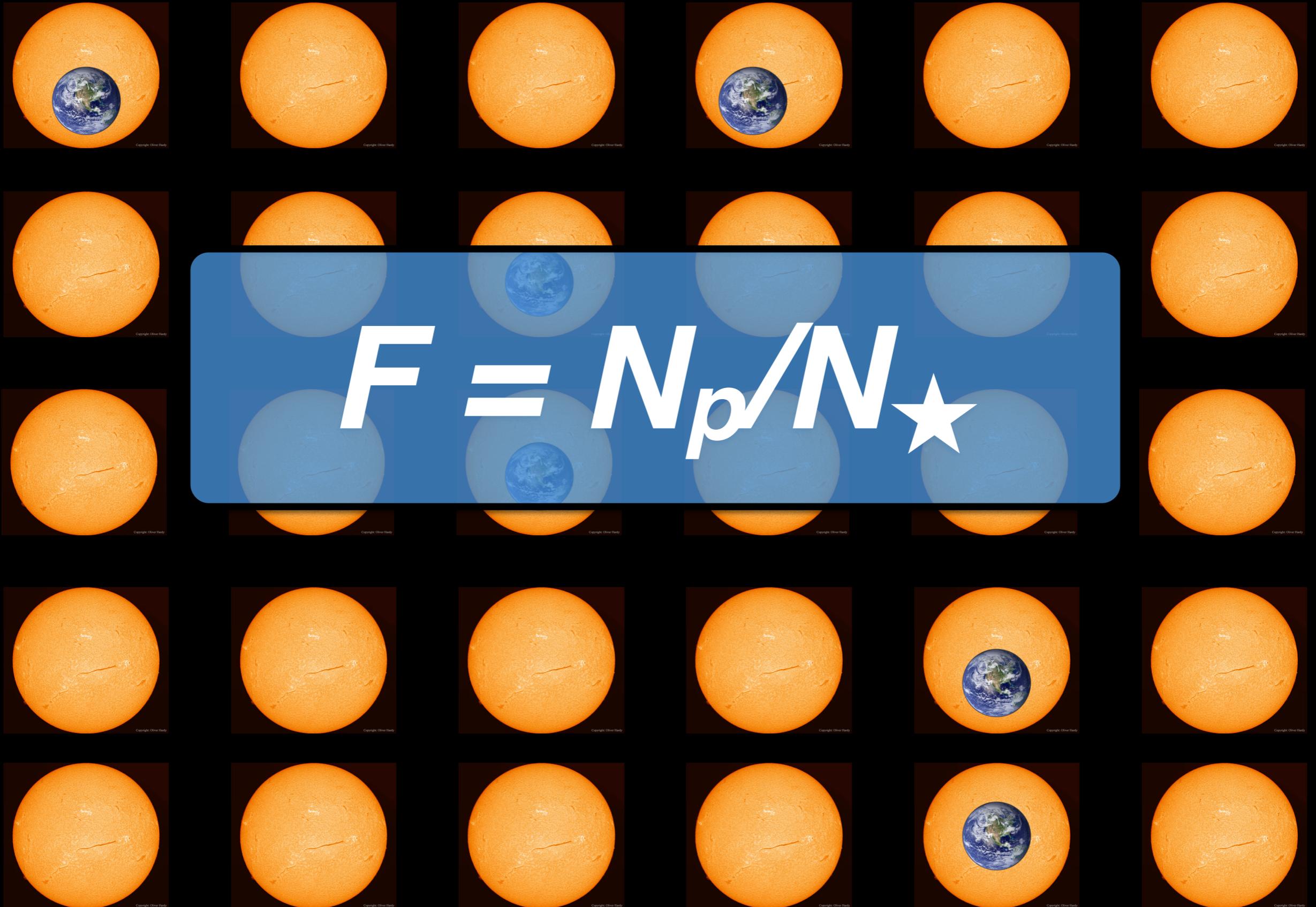
# Planet Occurrence Rates



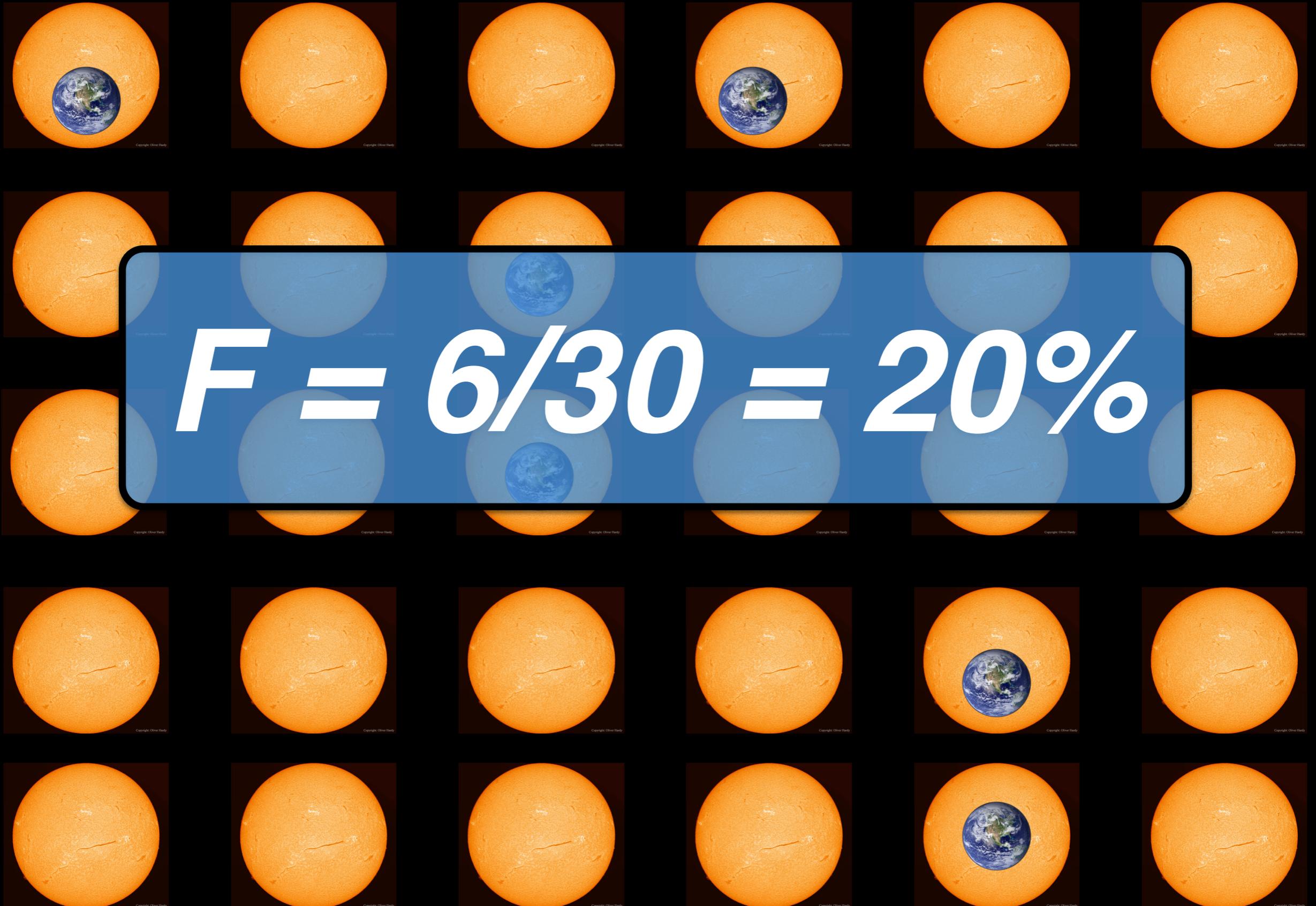
# Planet Occurrence Rates



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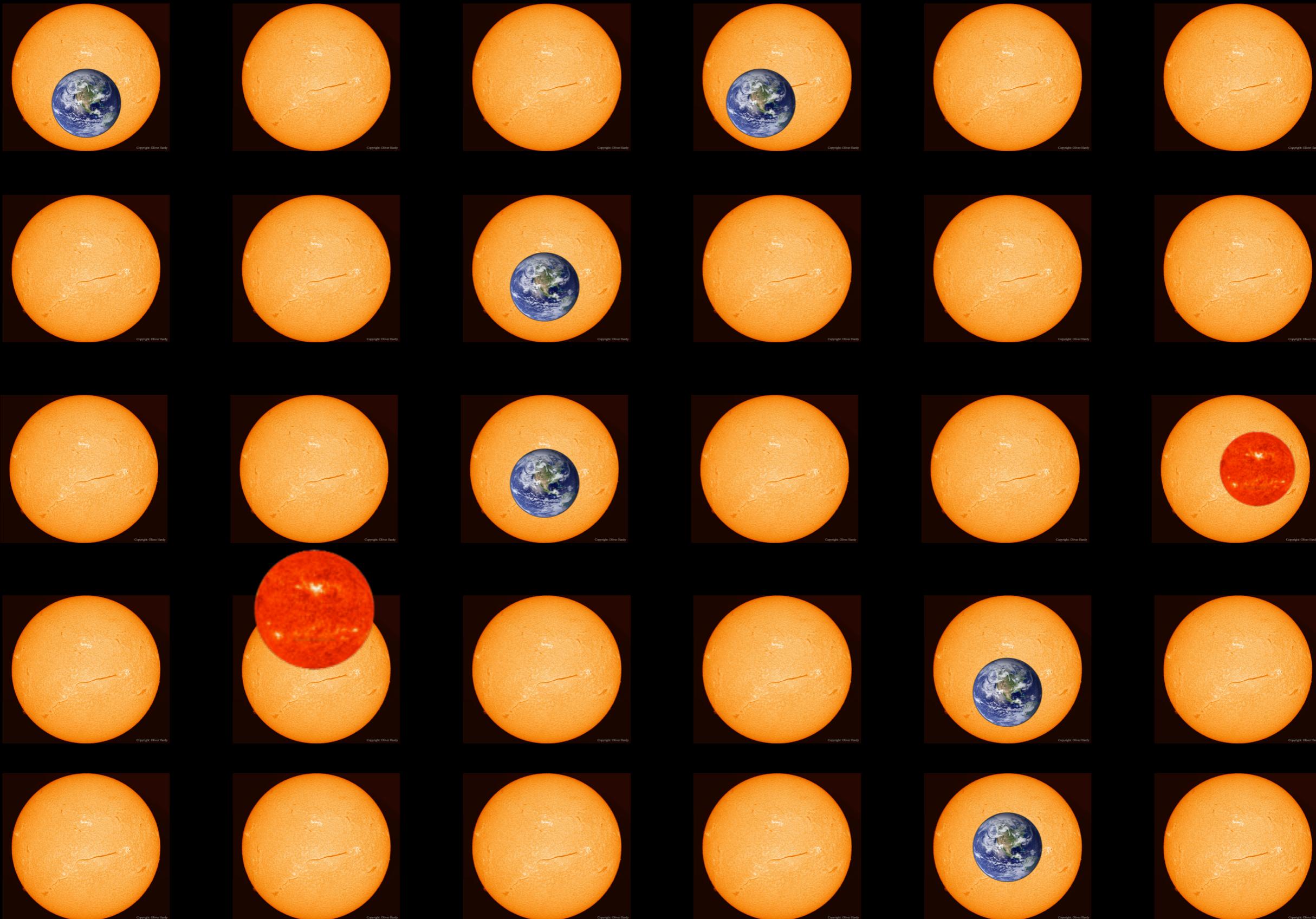


$$F = 6/30 = 20\%$$

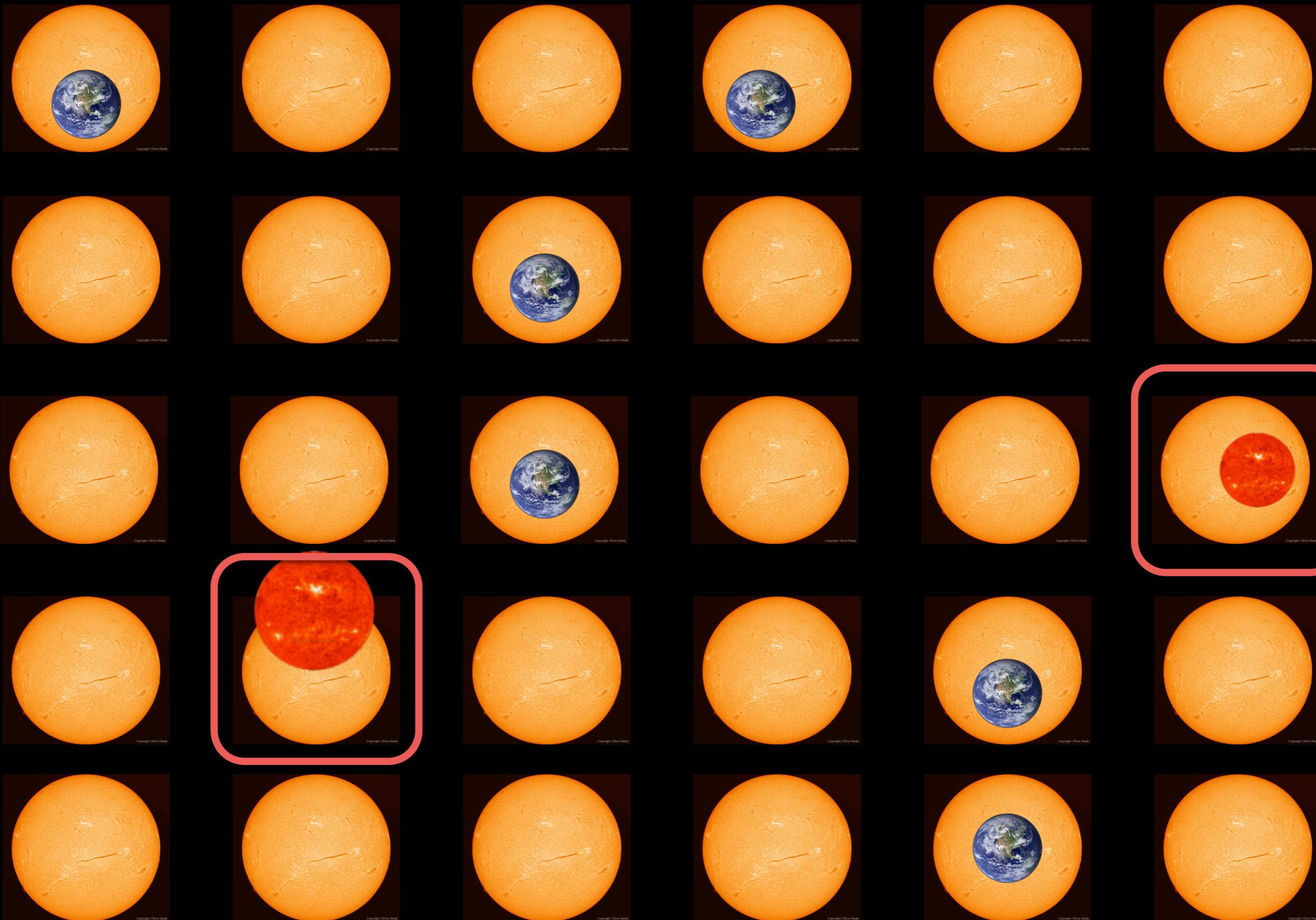




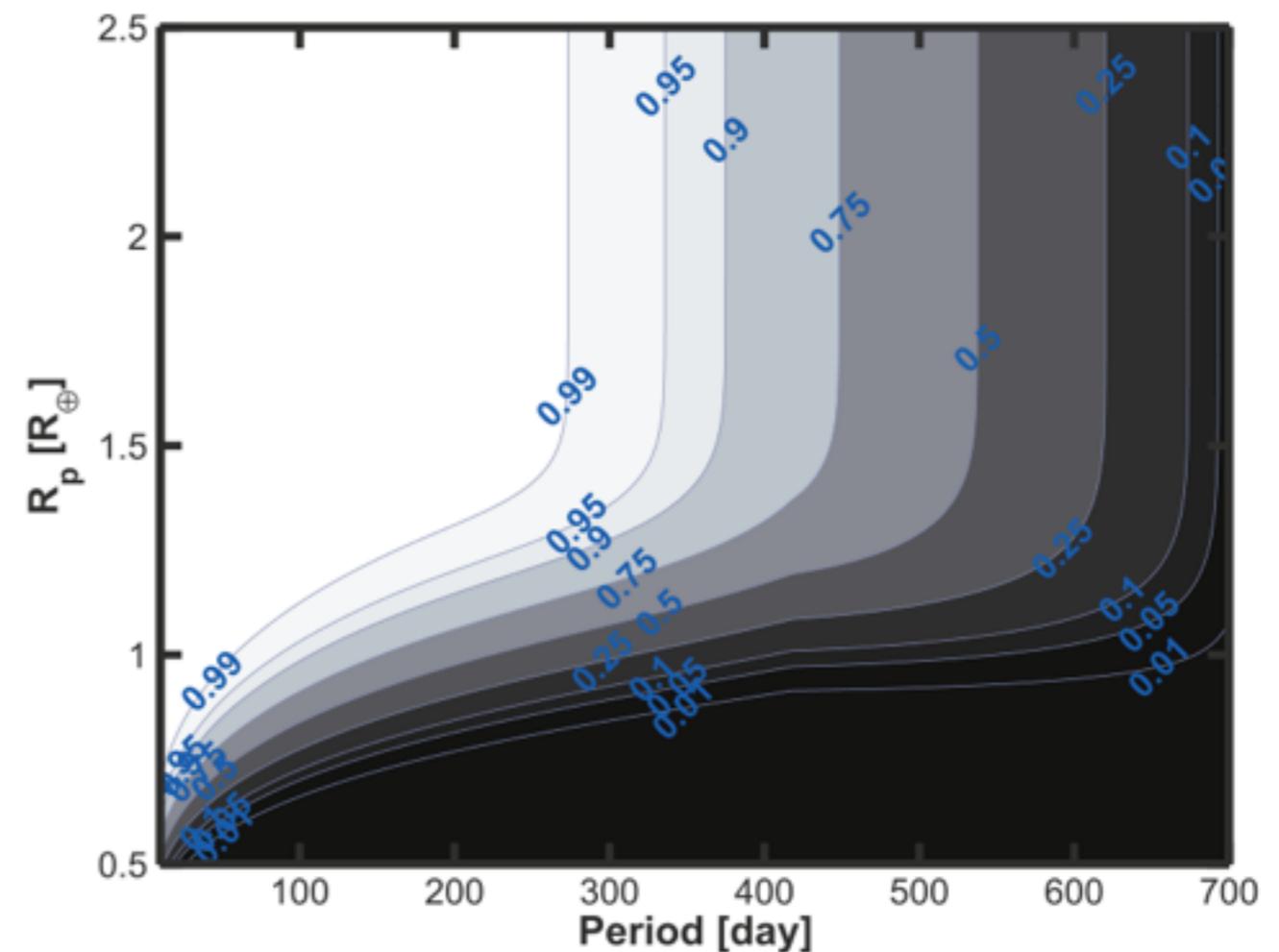
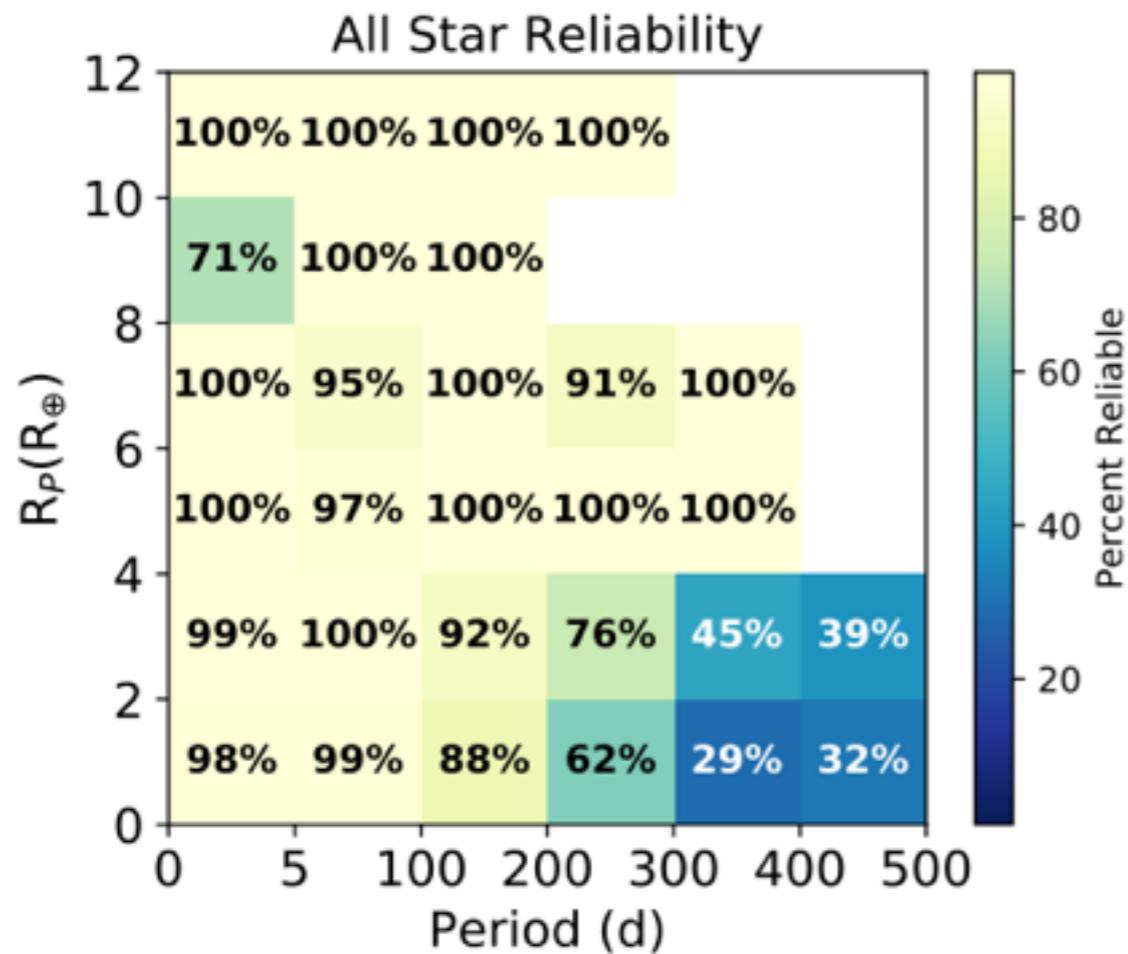
# Reliability



# Reliability



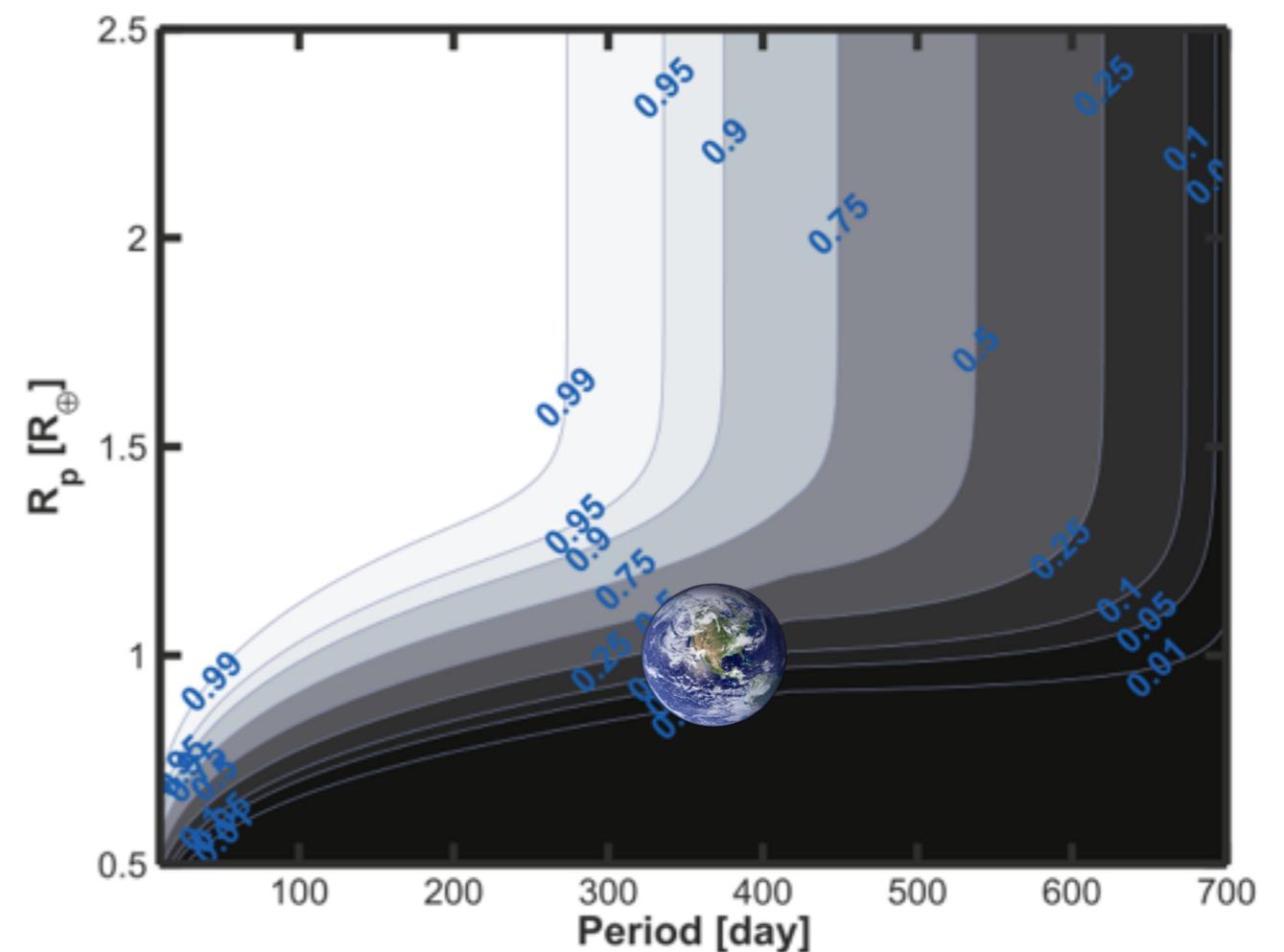
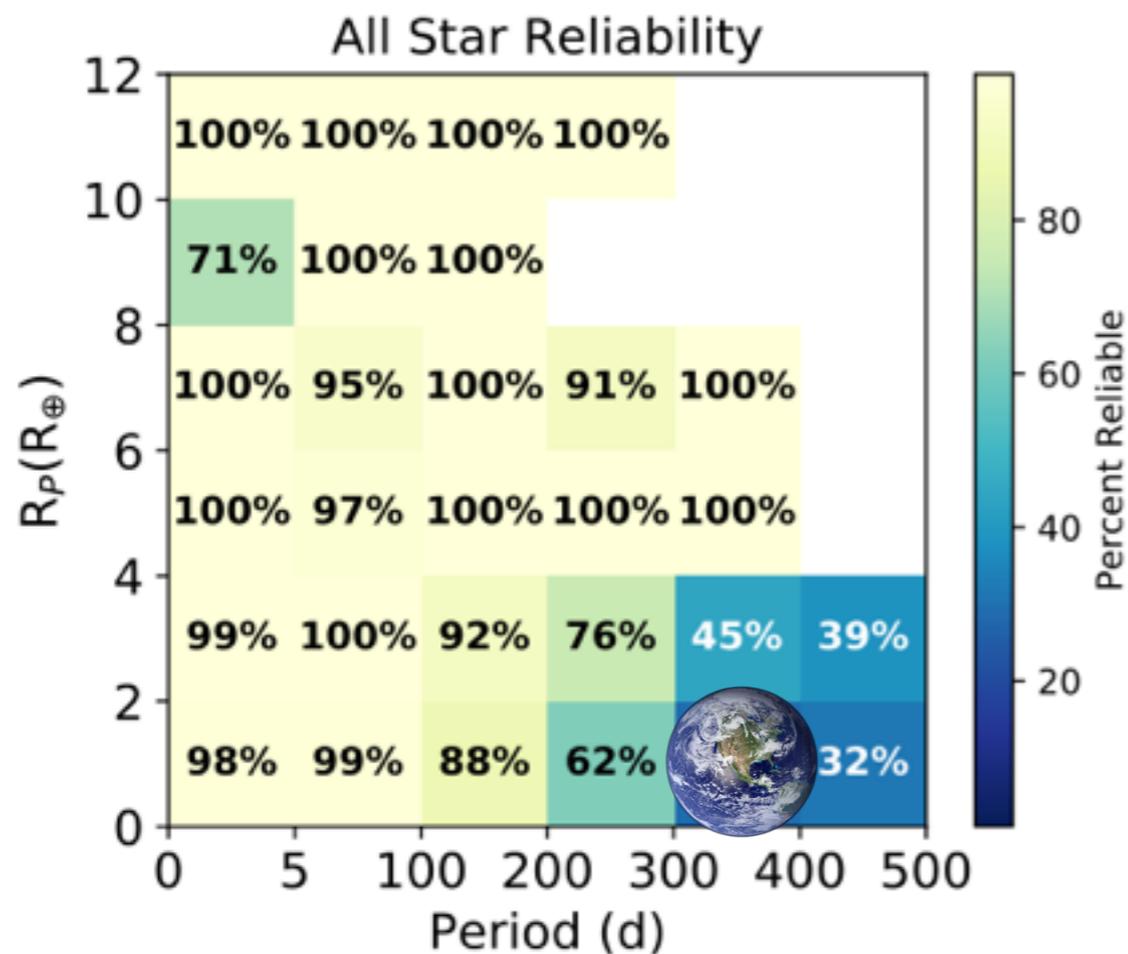
# Kepler is incomplete and unreliable at the limits of its sensitivity.



Thompson+2017

Burke+2015

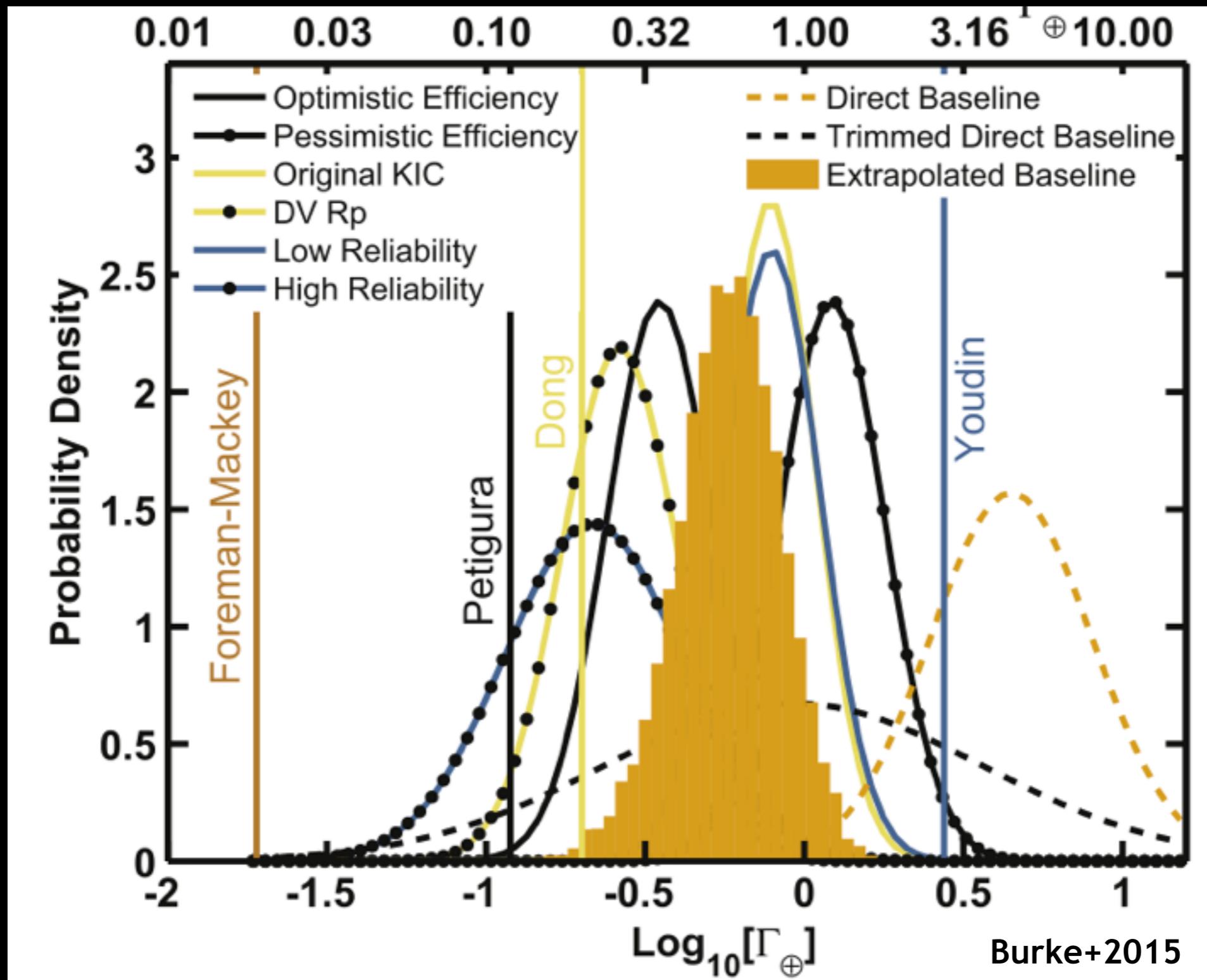
# *Kepler* is incomplete and unreliable for Earth-sized planets in Earth-like orbits.



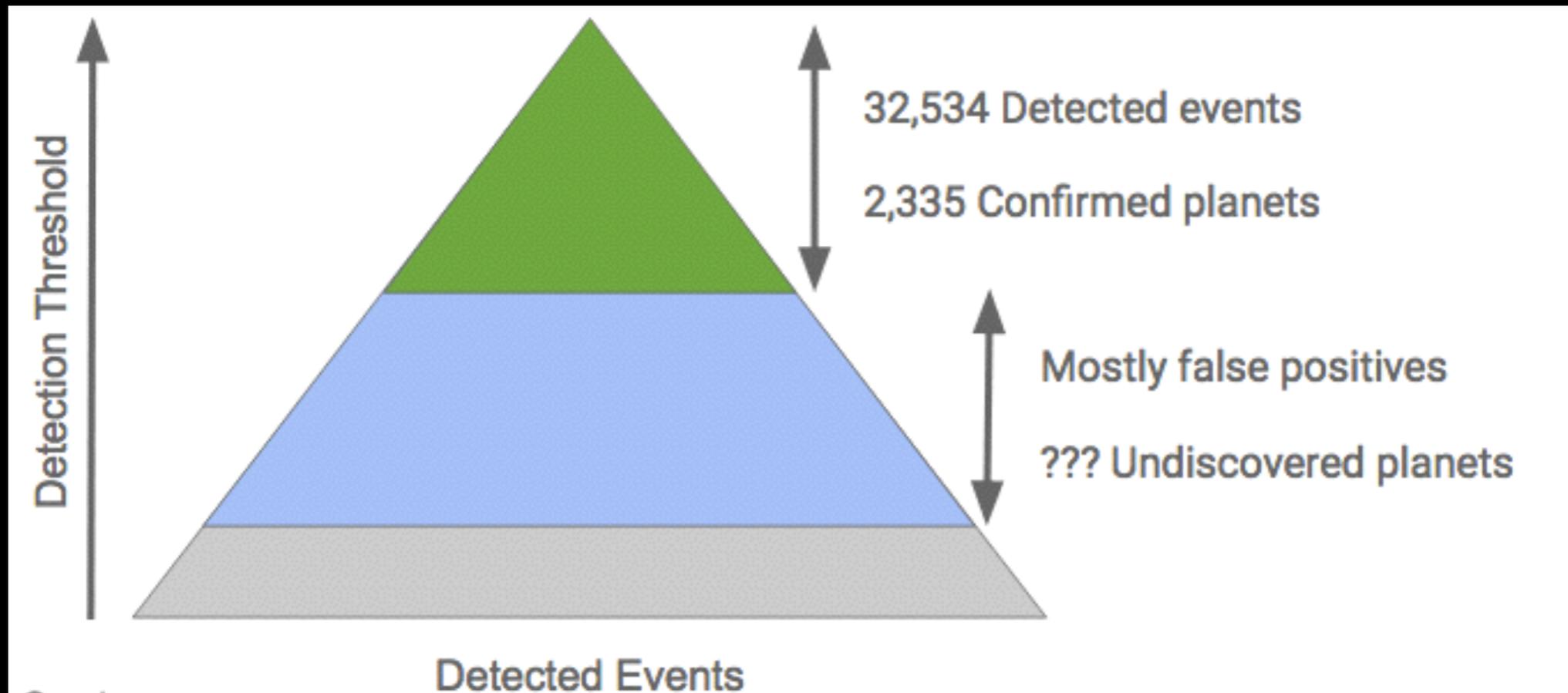
Thompson+2017

Burke+2015

# There is an order of magnitude uncertainty on the occurrence of Earths around Sun-like stars

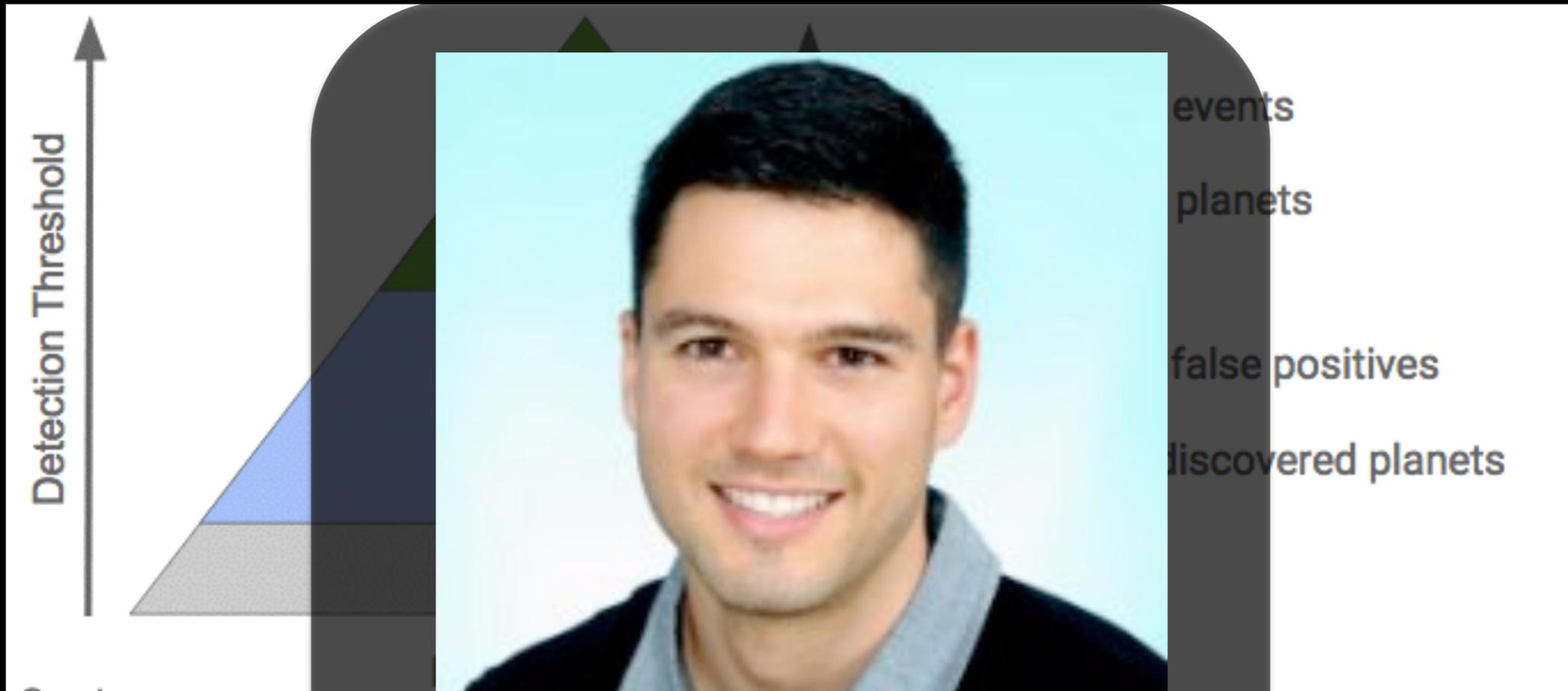


# Our Approach



- 1. Increase sensitivity (and therefore completeness) by allowing weaker signals to be considered as planet candidates, at the cost of a higher false positive rate.
- 2. Use deep learning to more effectively distinguish real signals from false alarms and false positives, keeping reliability high.

# Our Approach



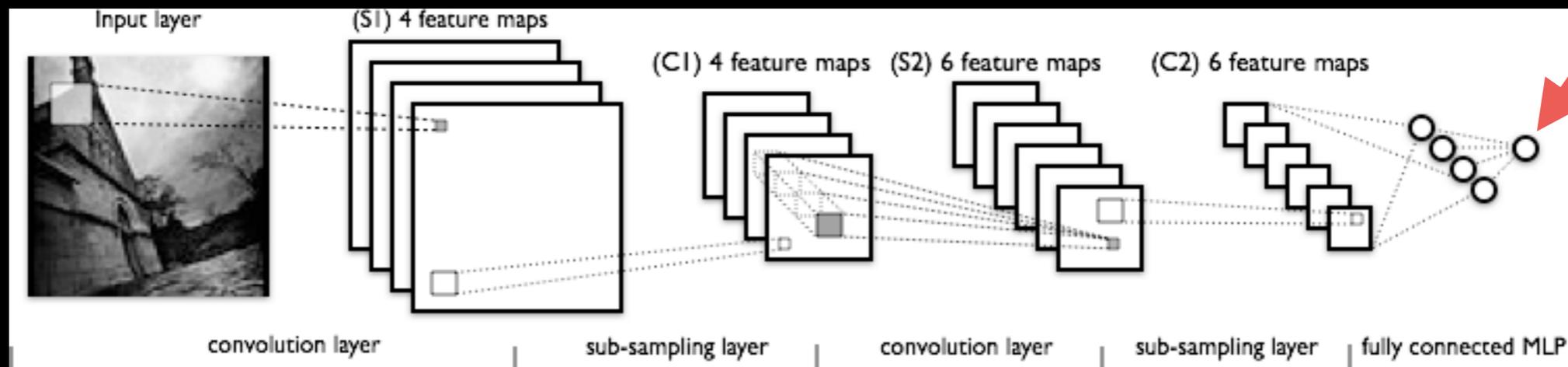
- 1. Increase sensitivity (and therefore completeness) by allowing weak signals to be considered as planet candidates, at the cost of a higher false positive rate.
- 2. Use deep learning to more effectively distinguish real signals from false alarms and false positives, keeping reliability high.

Chris Shallue

Google Brain

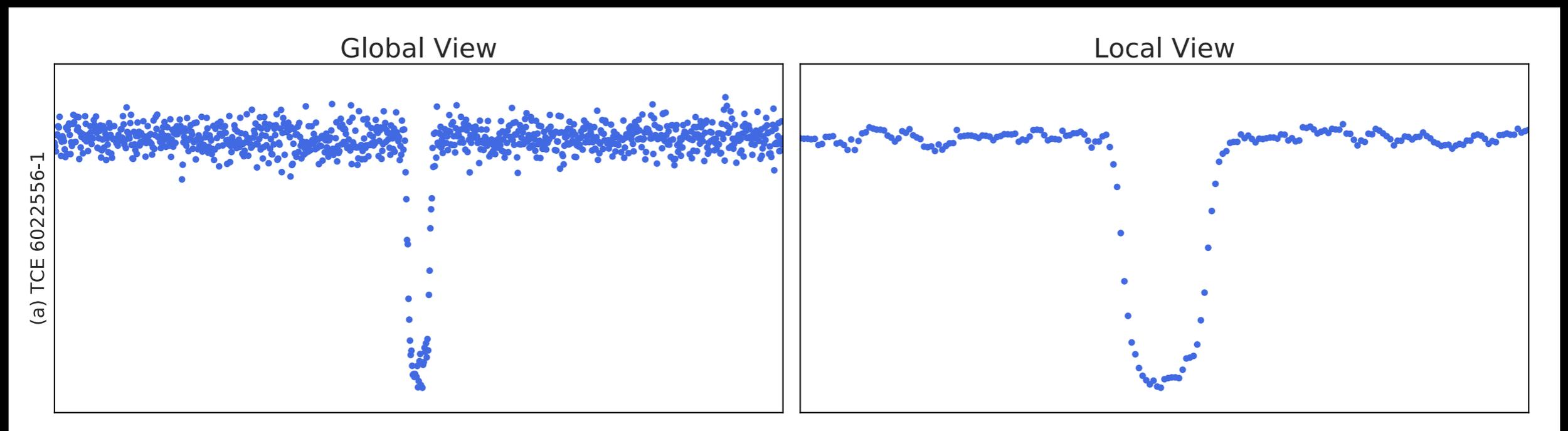
# Deep Learning

Given some image/vector as input, perform math operations which convert the image to an output.



The operations are “learned” by minimizing some cost function which compares data from a training set to their known classification.

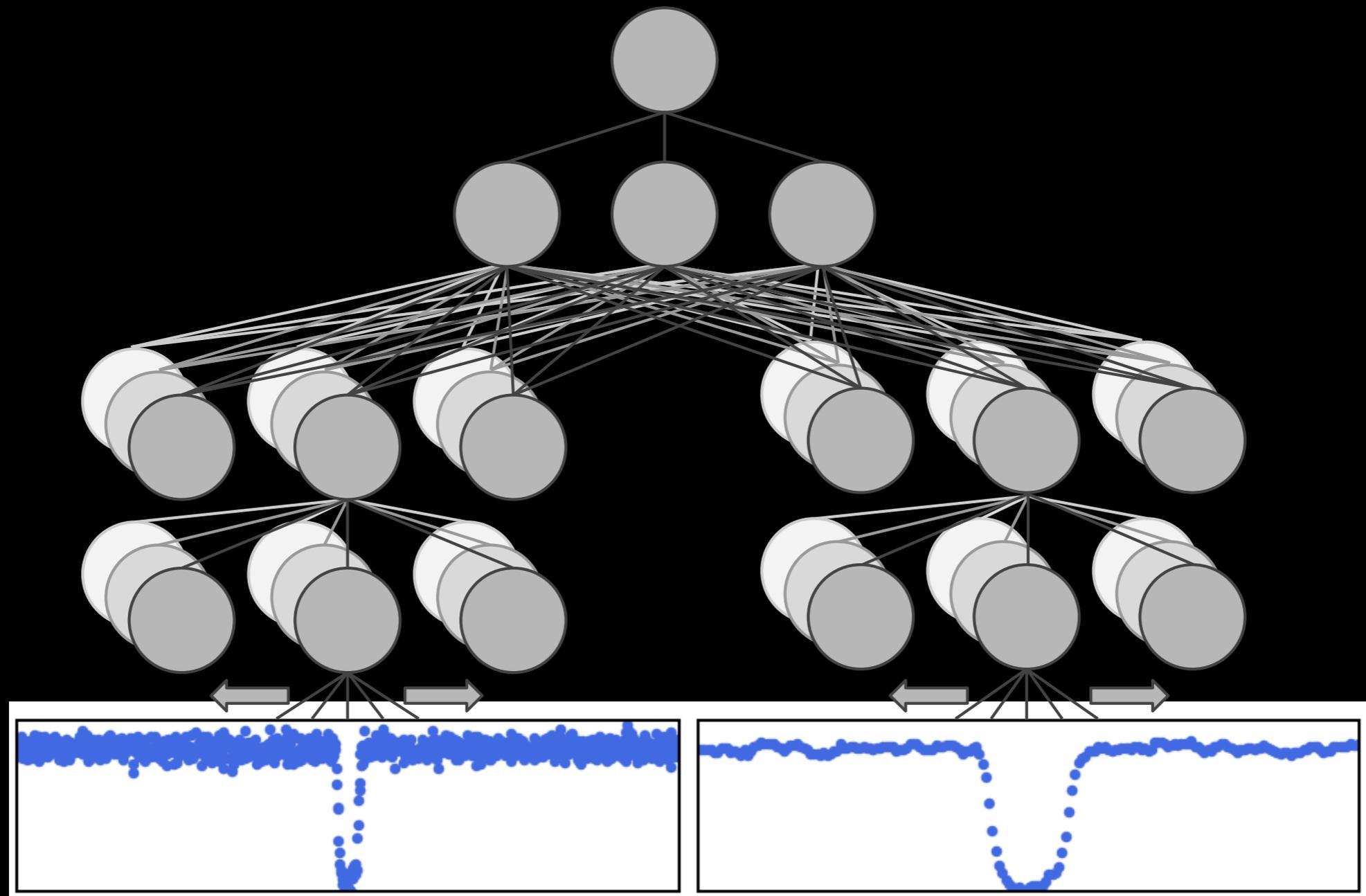
# Inputs: binned and phase-folded *Kepler* light curves



**Global View:**  
shows phase-variations,  
secondary eclipses, etc

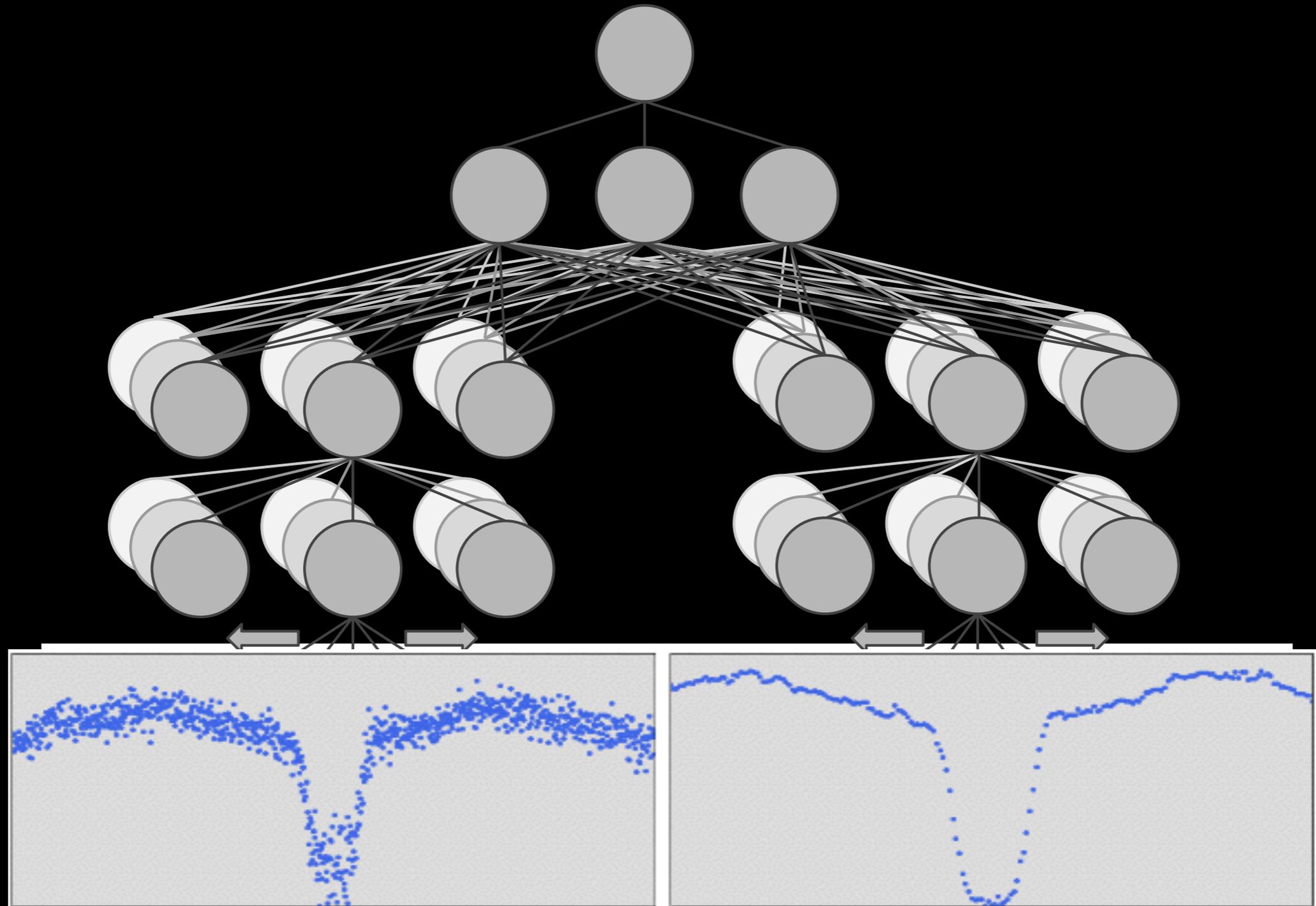
**Local View:** close-up  
look at the transit

# Proof of Concept Neural Network for Planet Vetting Planet



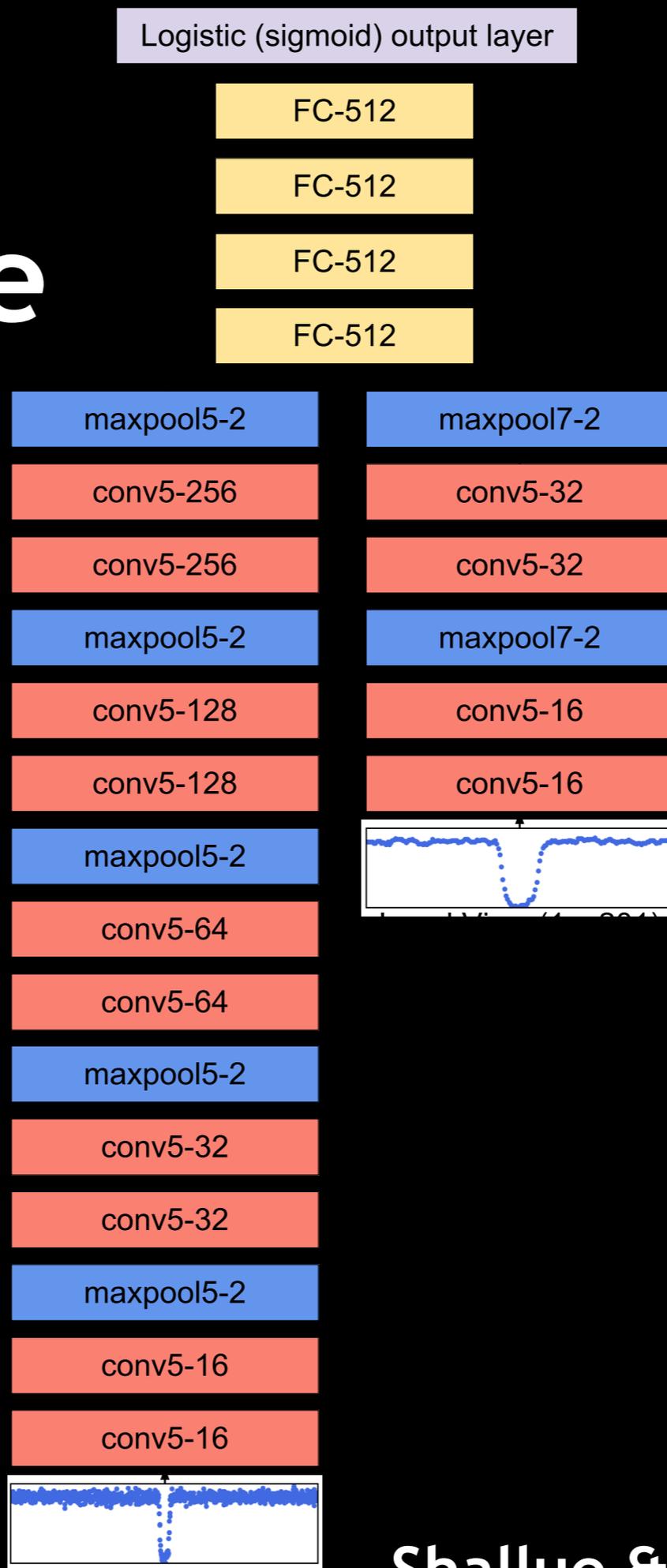
# Proof of Concept Neural Network for Planet Vetting

## Not a Planet



Shallue & Vanderburg (submitted)

# Network Architecture



Shallue & Vanderburg (submitted)

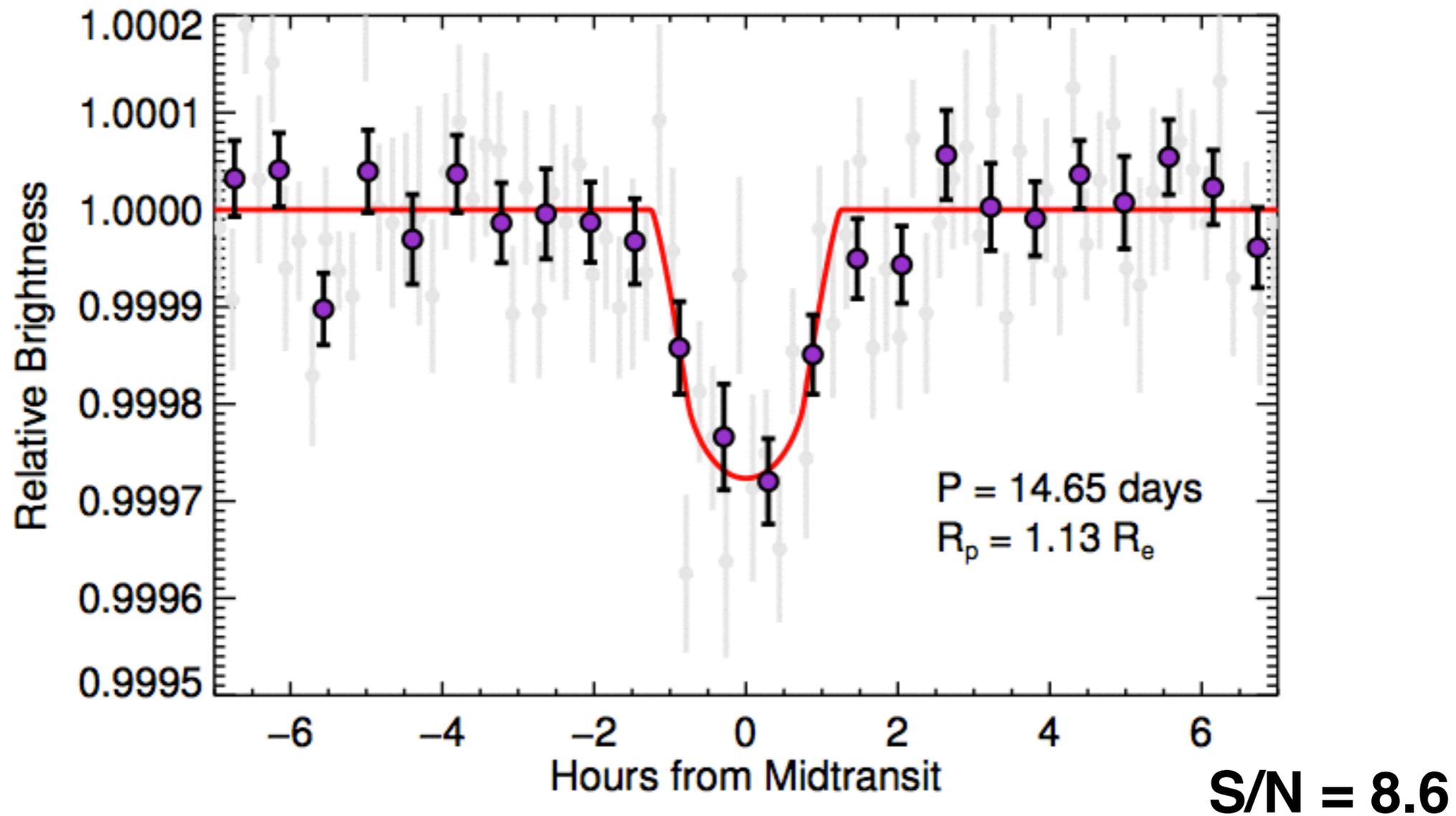
# Results

	AUC	Accuracy
Our work	<b>0.988</b>	0.960
Coughlin et al. (Robovetter)	0.974	<b>0.974</b>
Armstrong et al.		0.87
McCauliff et al. (Autovetter)	(0.997)* not held-out results	(0.986)* not held-out results

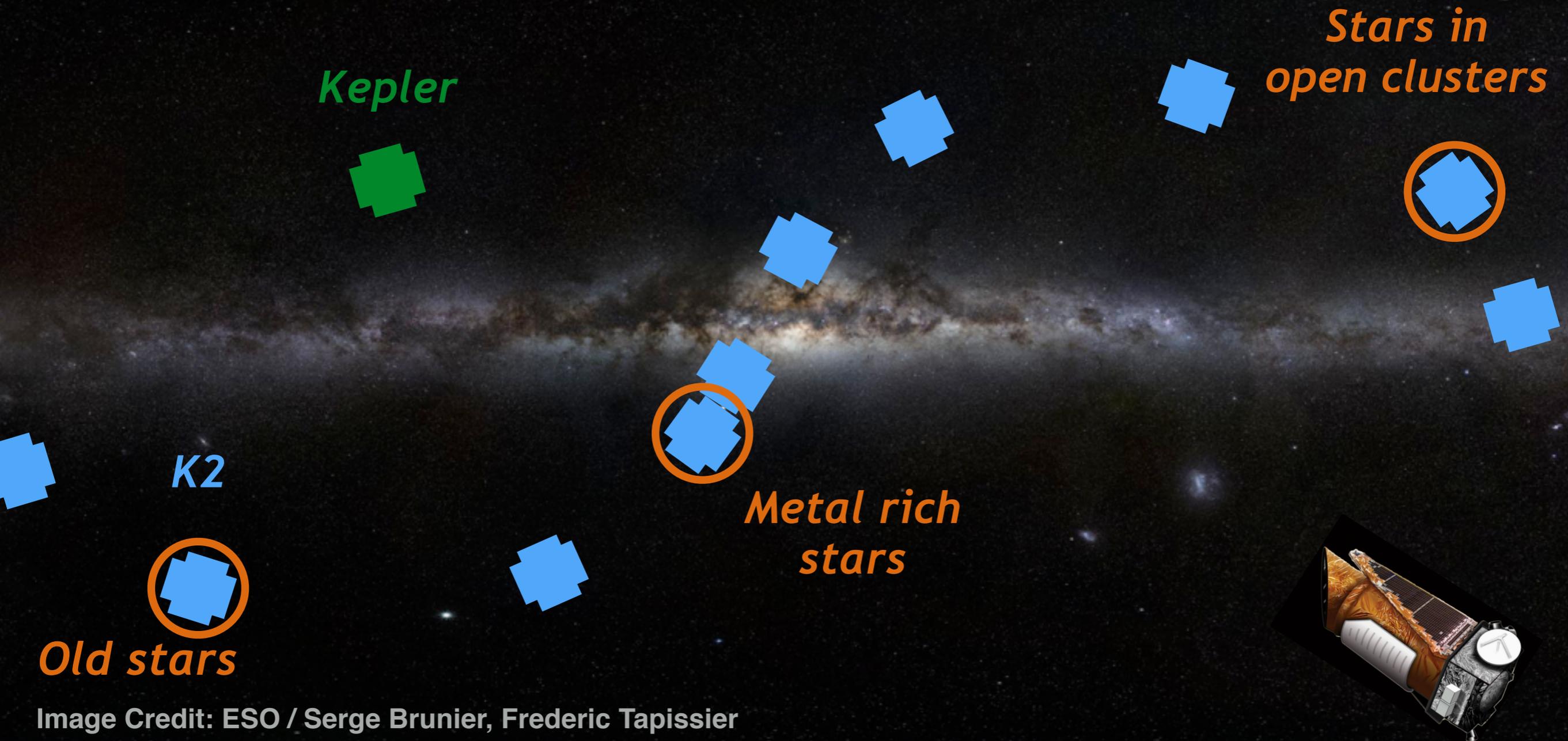
**Comparable to industry standards like Robovetter, but work necessary to incorporate other information as inputs (difference images, quarterly depth variations, etc.)**

**Shallue & Vanderburg (submitted)**

# Proof of concept search of Kepler multiplanet systems

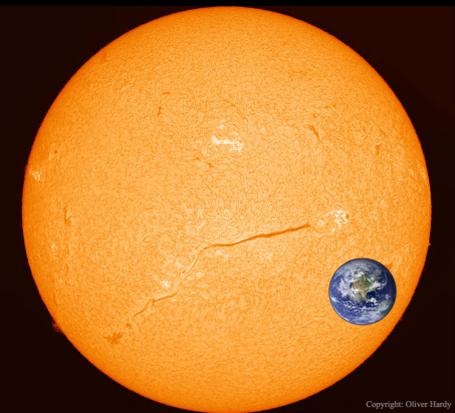


# Can we study planet occurrence with the K2 mission?



How do planetary systems vary in different galactic environments?

**Occurrence rates with K2 are challenging for several reasons, including inhomogenous stellar parameters.**



Copyright: Oliver Hardy

# Spectra of 275 K2 candidates from Whipple Observatory (Mt. Hopkins)



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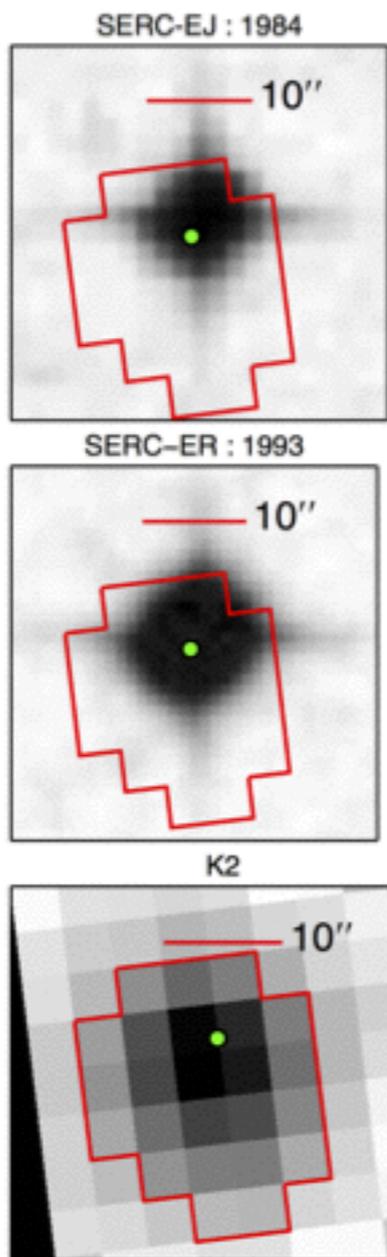
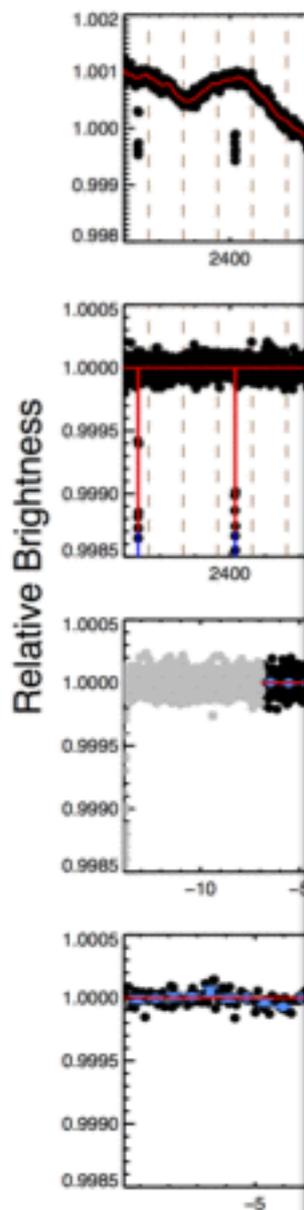
→ UC Berkeley grad (Fall 2018)

# Planet Candidate Vetting and Validation

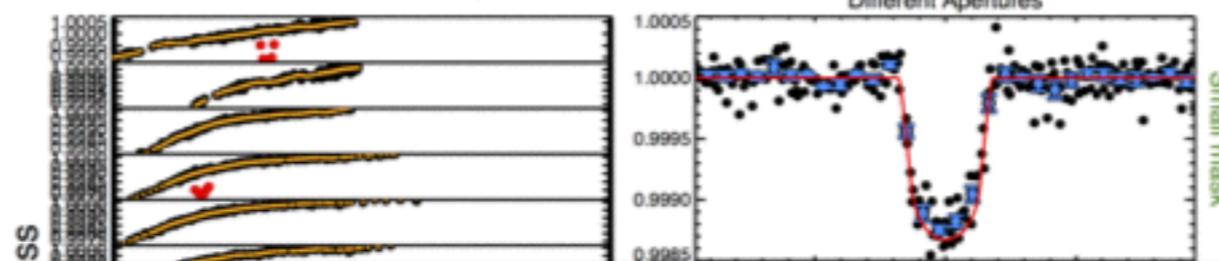
Mayo, Vanderburg, +  
(in prep)

EPIC 212521166, Candidate 1 of 1

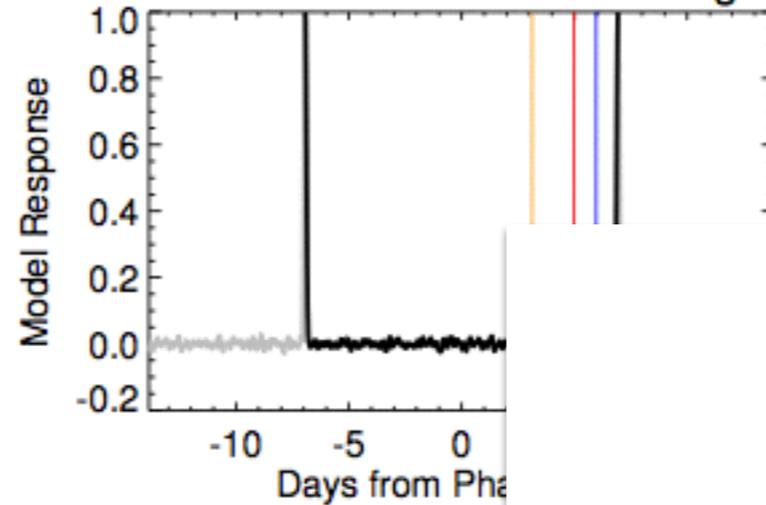
EP 212521166, Cand. 1 of 1  
Campaign 6  
Period = 13.863953 days  
Duration = 3.2 hours  
Impact = 0.31  
R/R<sub>L</sub> = 0.0331  
Depth = 0.133%



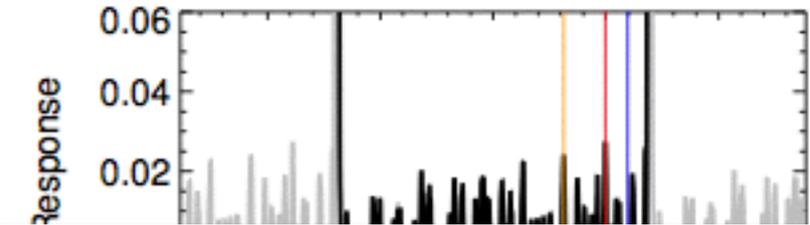
EPIC 212521166, Candidate 1 of 1



EPIC 212521166.01: 106.7 sigma



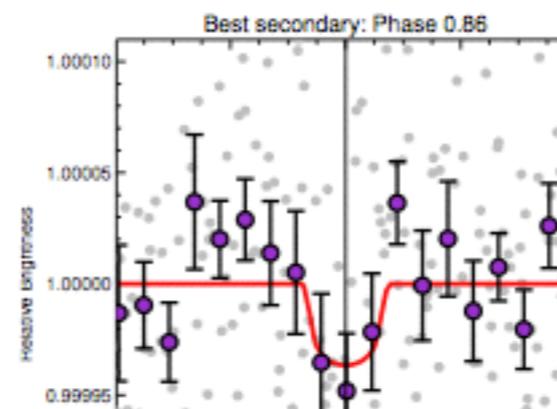
Detail out of transit



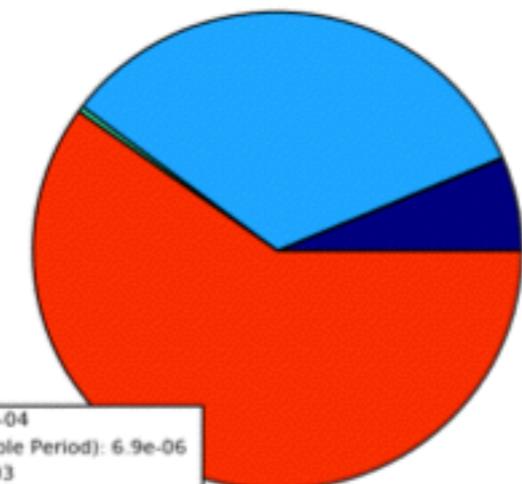
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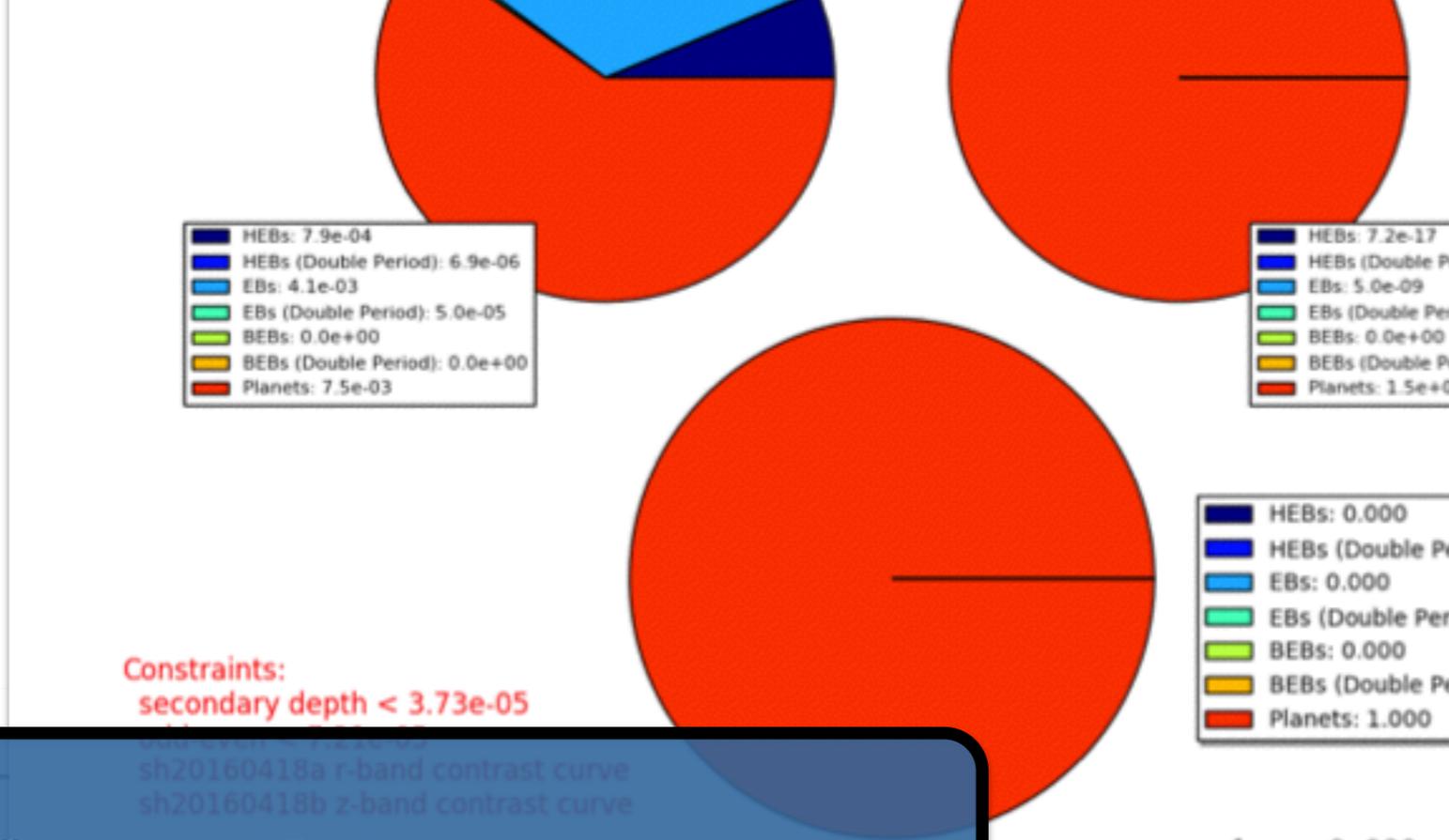
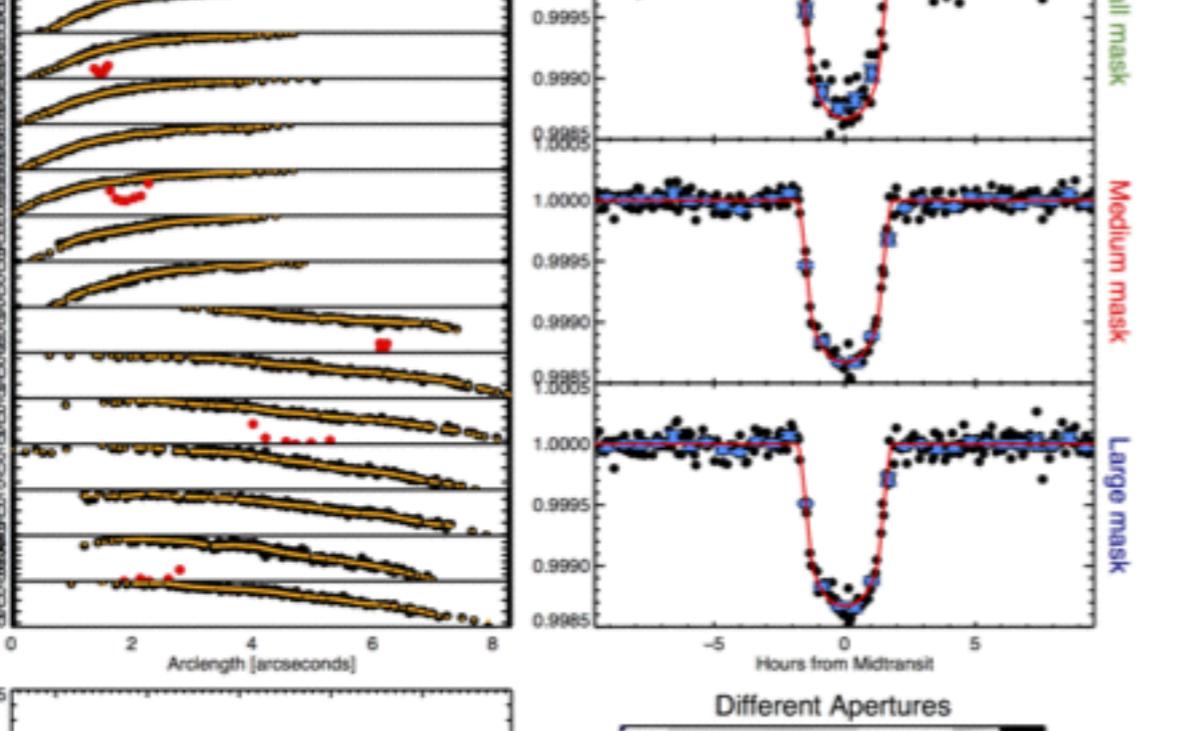
Priors

Lik



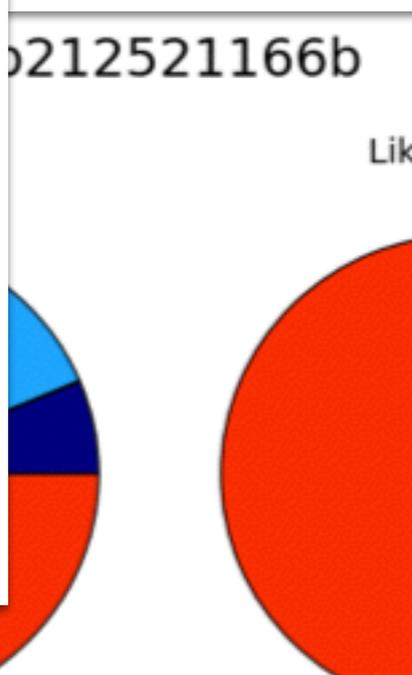
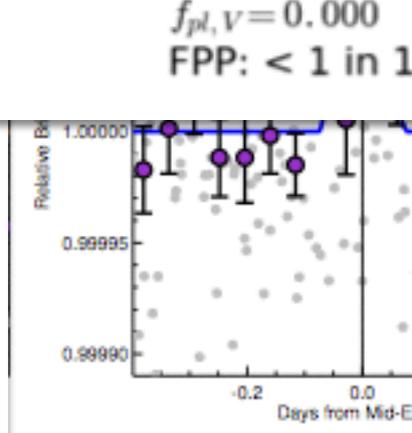
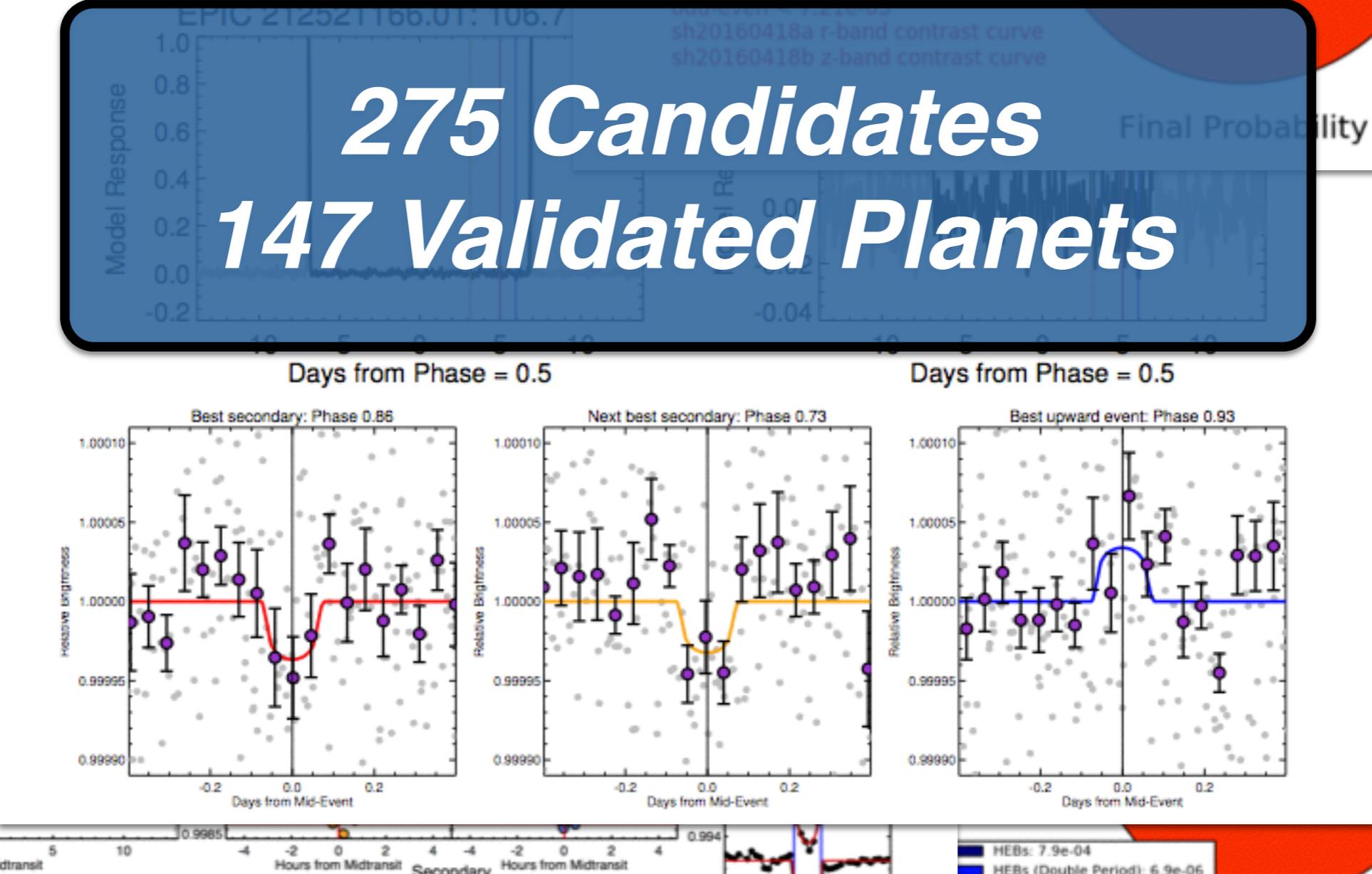
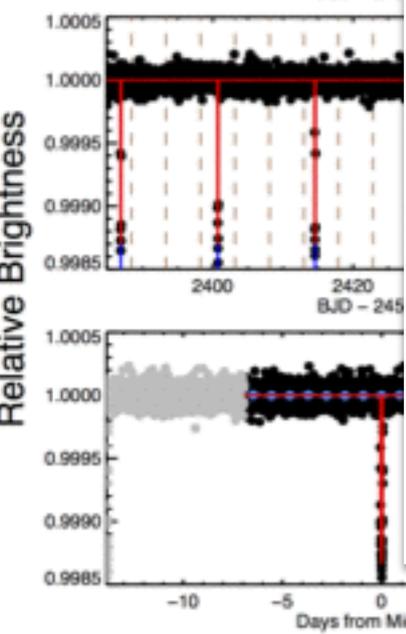
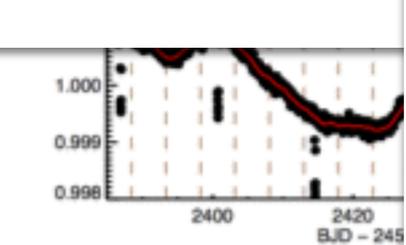
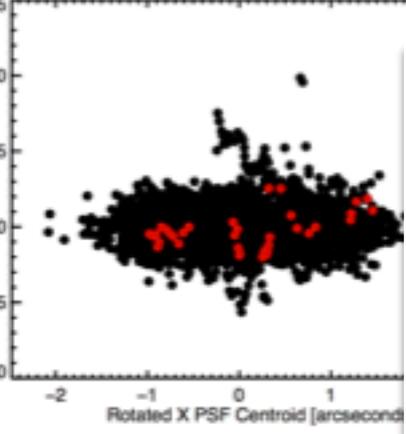
HEBs: 7.9e-04  
HEBs (Double Period): 6.9e-06  
EBs: 4.1e-03





Constraints:  
secondary depth < 3.73e-05

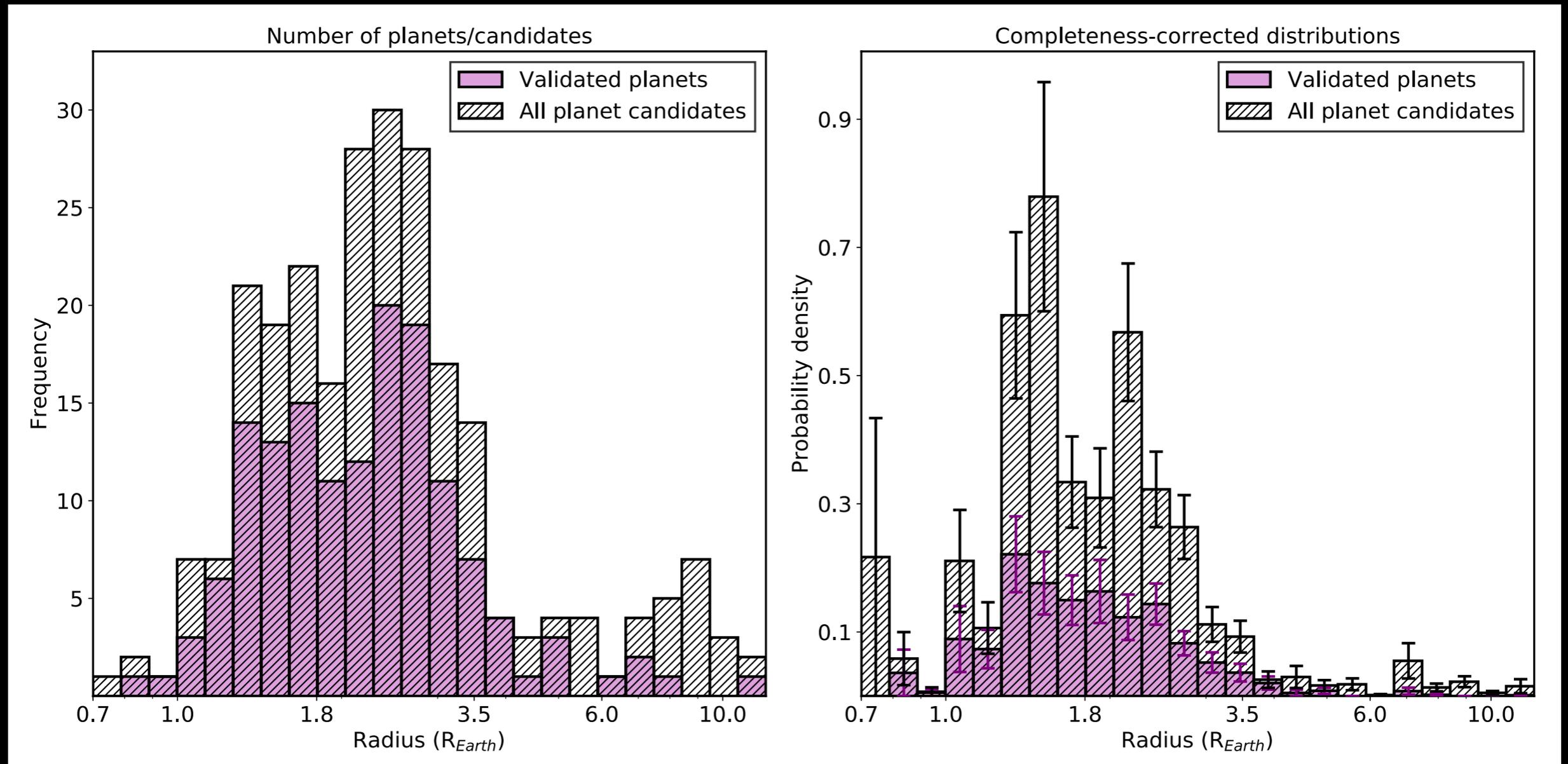
# 275 Candidates 147 Validated Planets



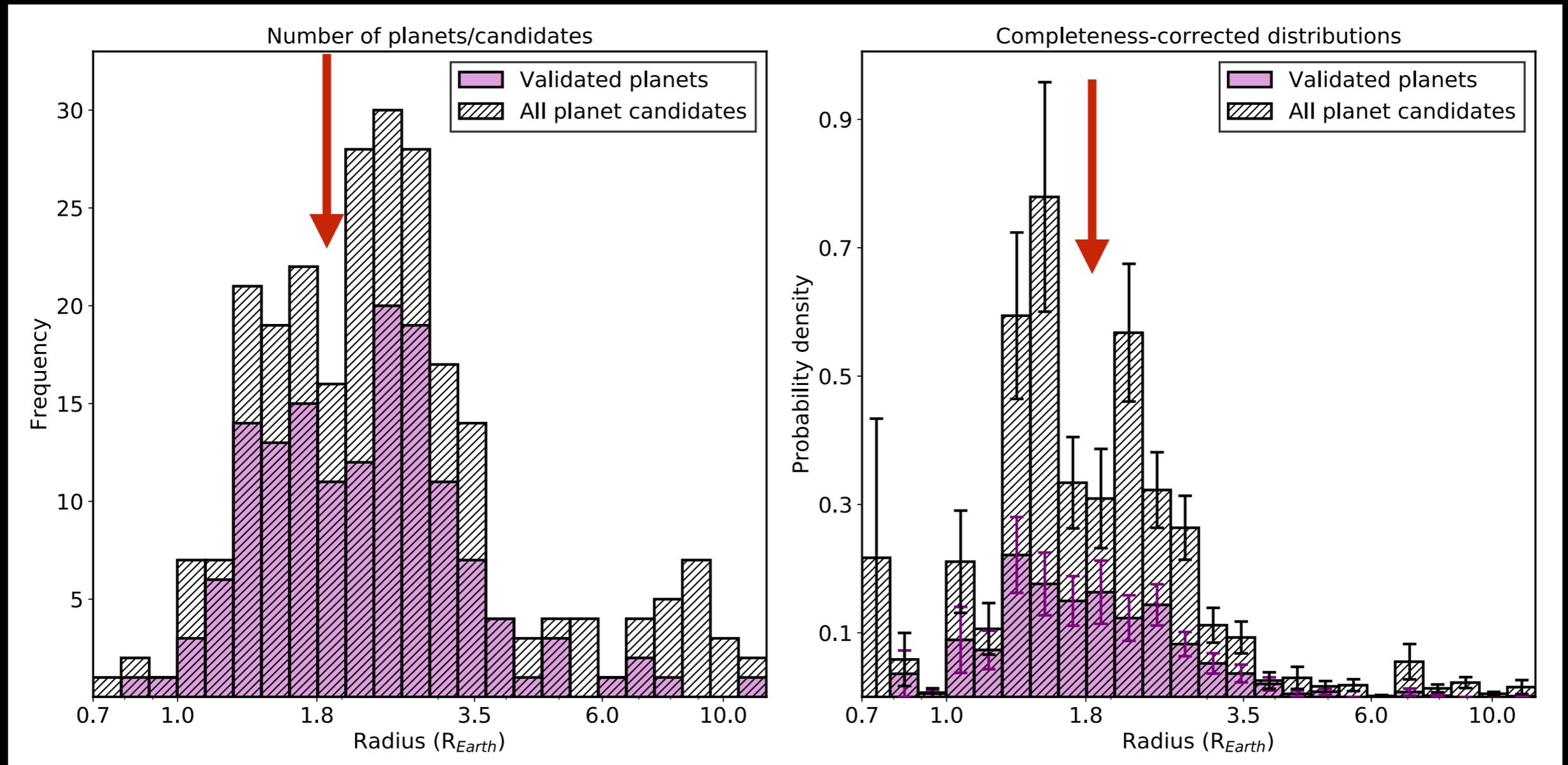
$f_{pl,v} = 0.000$   
FPP: < 1 in 1

HEBs: 7.9e-04  
HEBs (Double Period): 6.9e-06  
EBs: 4.1e-03

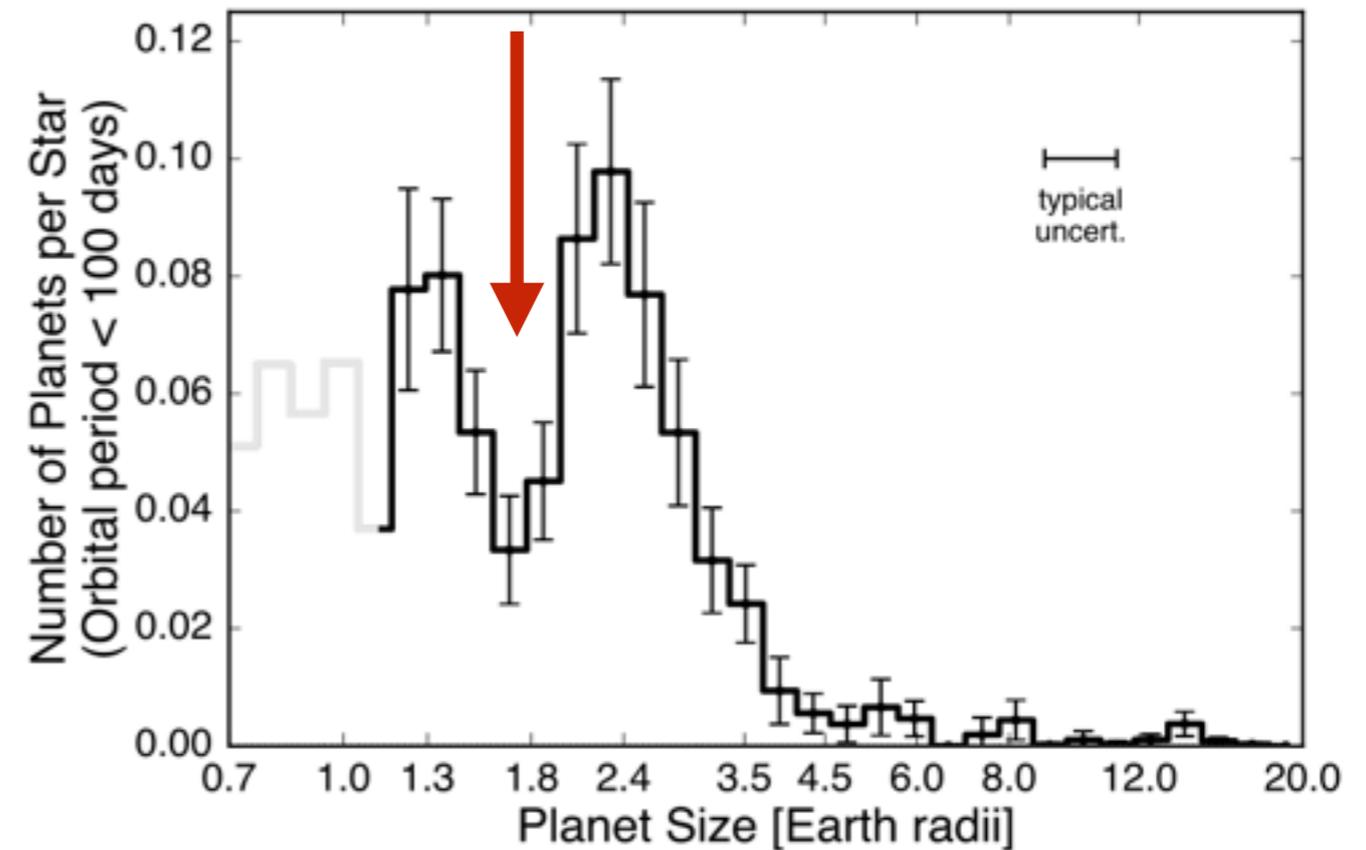
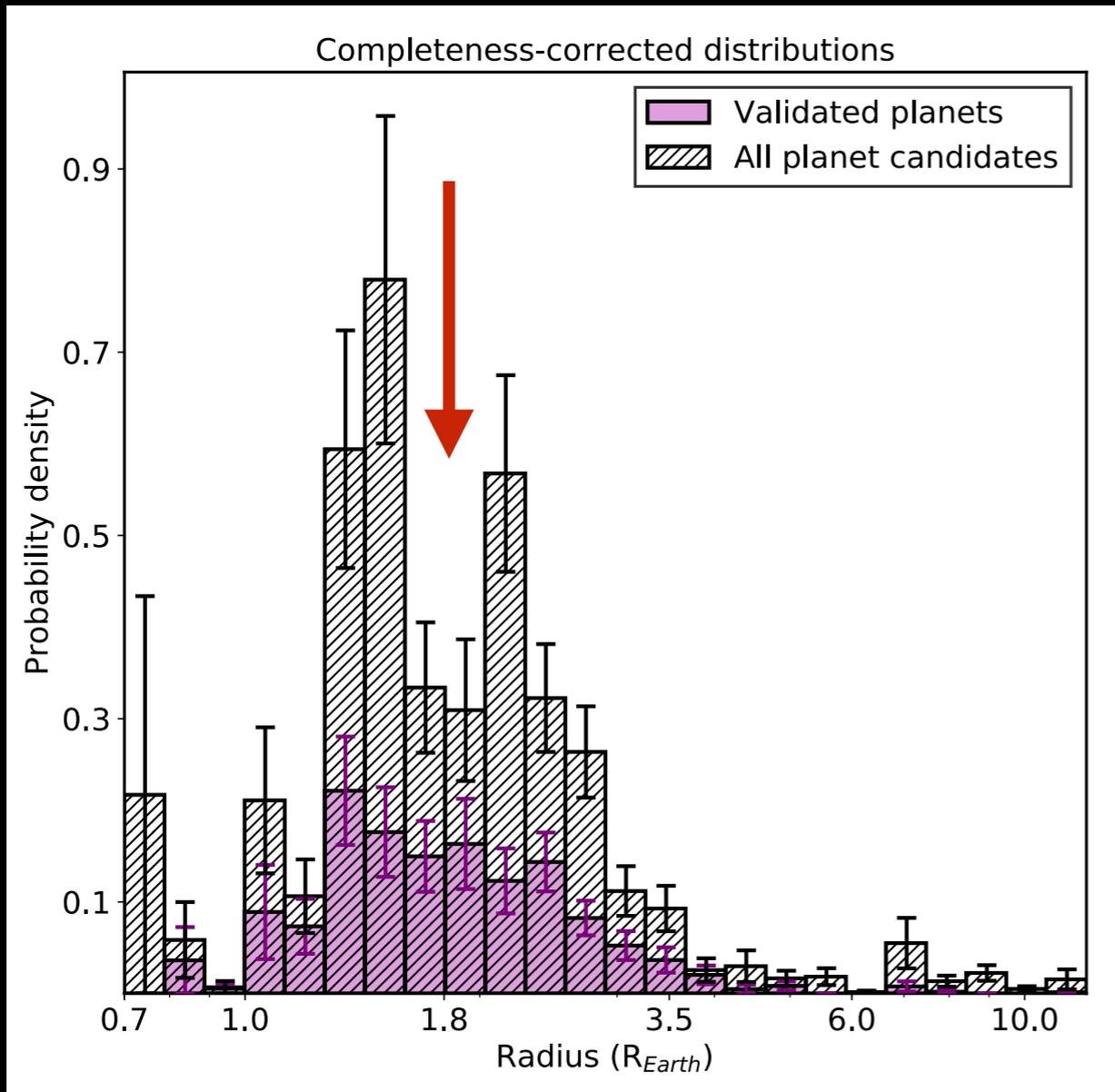
# Planet Radius Distribution



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Mayo, Vanderburg+ (in prep)

Fulton+2017

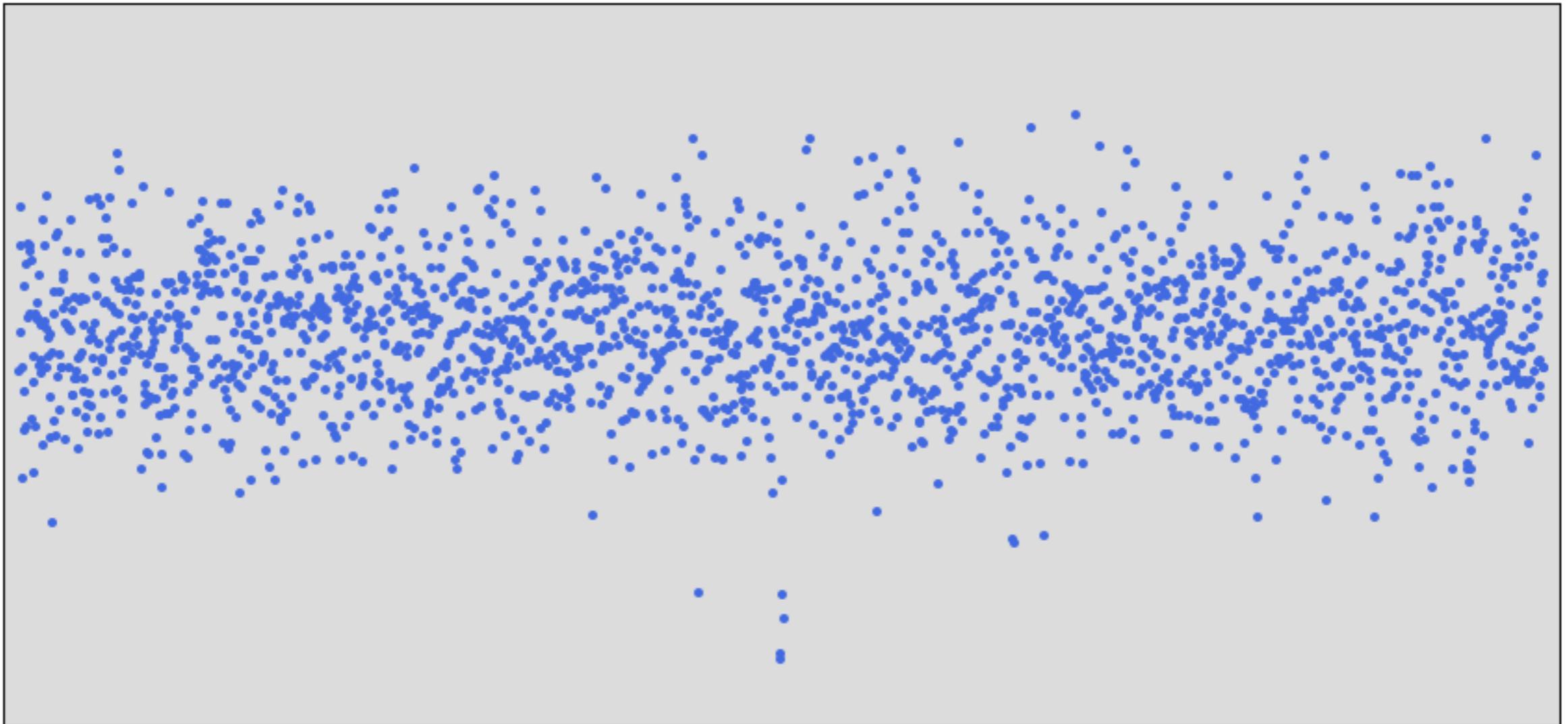
# Conclusions

- We have used deep neural networks to vet Kepler planet candidates and achieved good results in a proof-of-concept test.
- By lowering detection thresholds and compensating for the increased number of false positives, we can improve Kepler's sensitivity to weak transit signals. We have detected new planets in Kepler multi-planet systems using this strategy.
- We are working towards occurrence studies with K2 data by carefully characterizing and vetting planet candidates and their host stars. We can see the first hint of the gap in the planet radius distribution in K2 data.

# Backup Slides

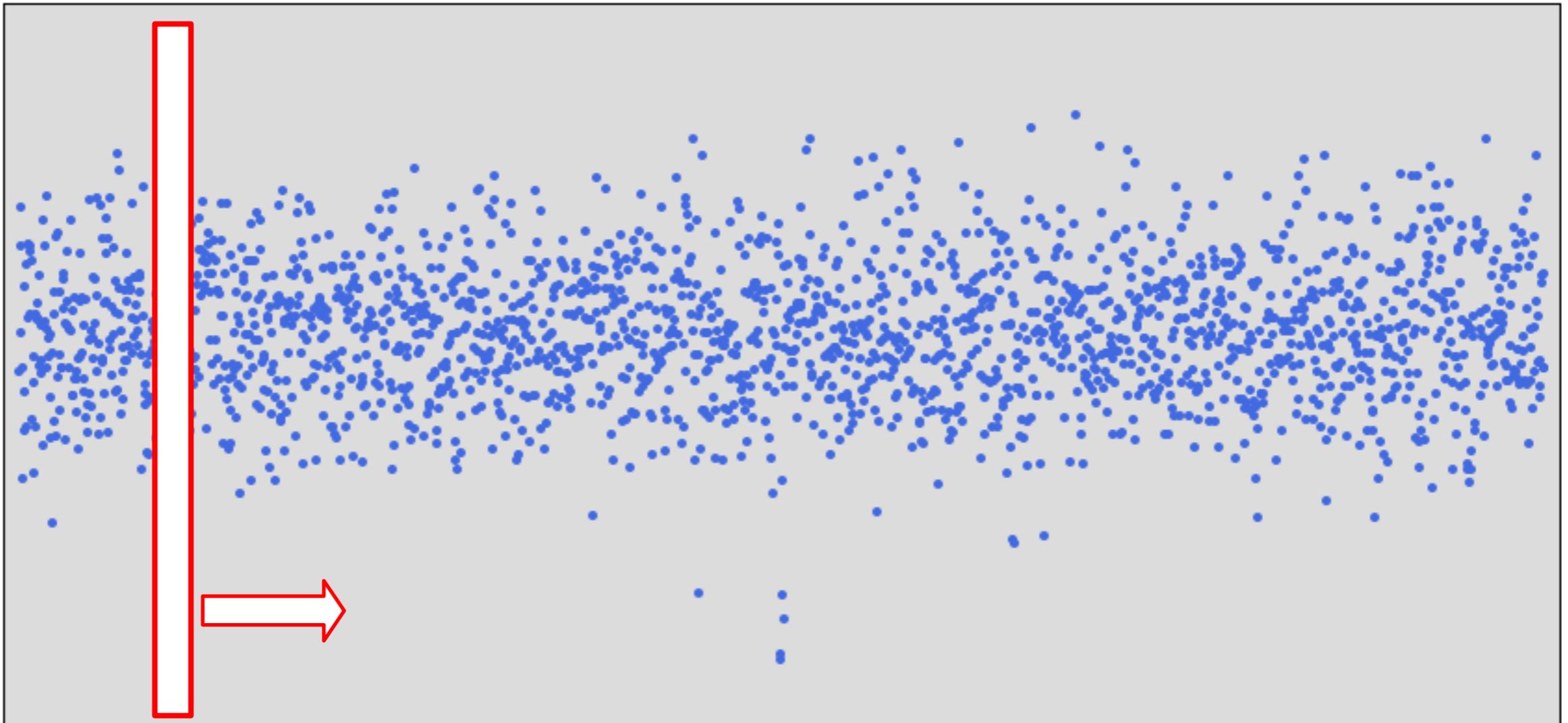
# Visualizing the Network's Decisions

TCE 5956342-4



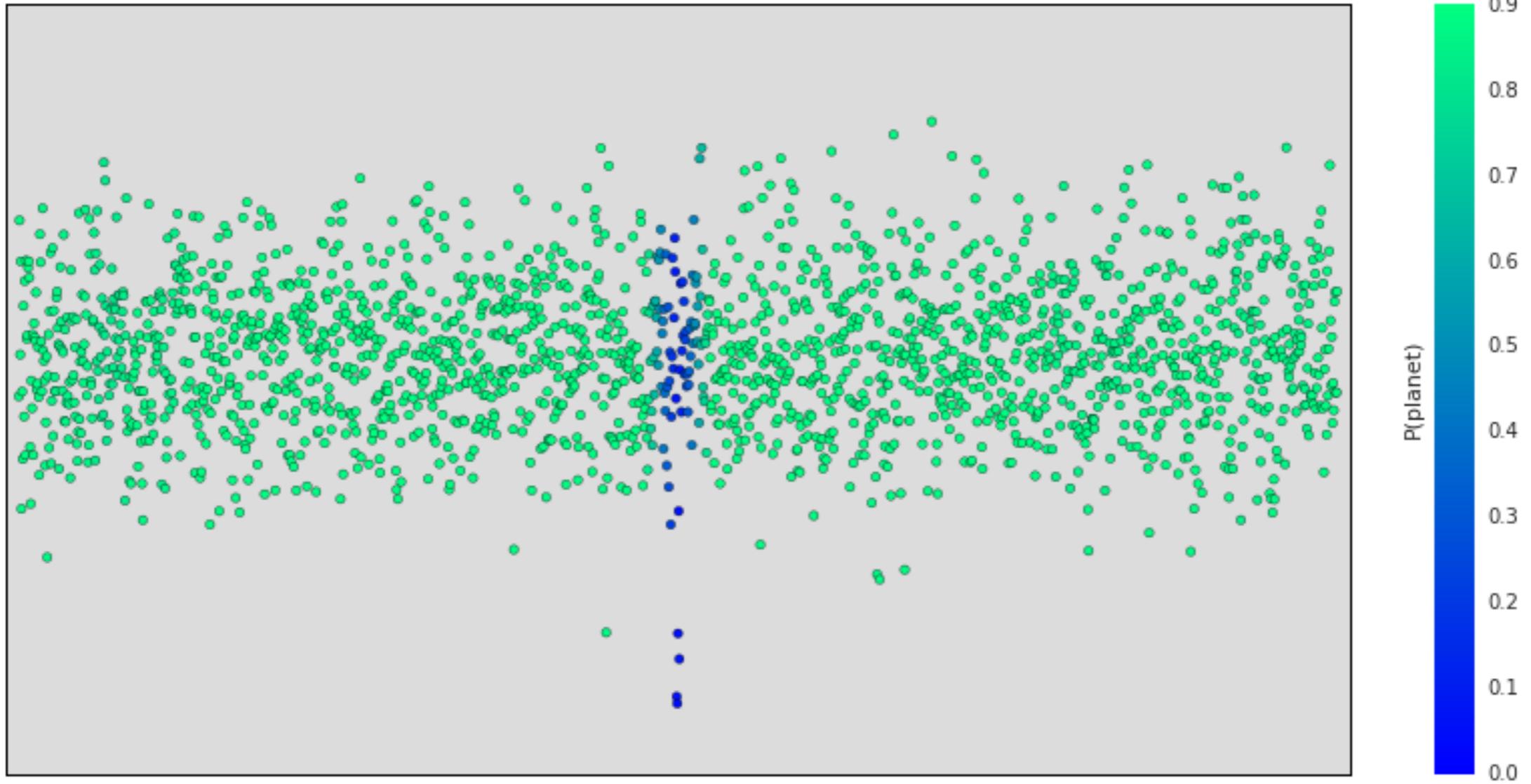
# Visualizing the Network's Decisions

TCE 5956342-4



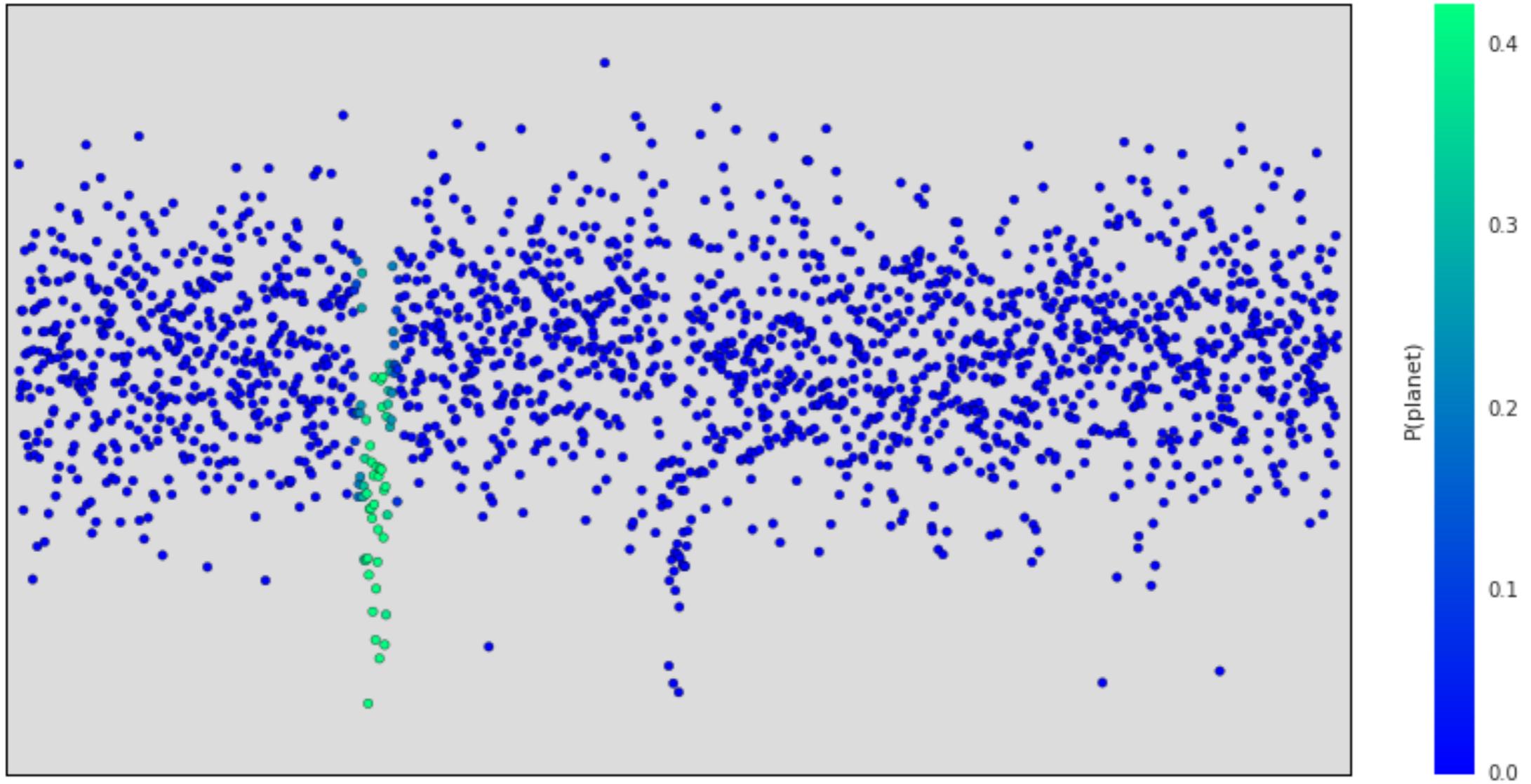
# Visualizing the Network's Decisions

TCE 5956342-4



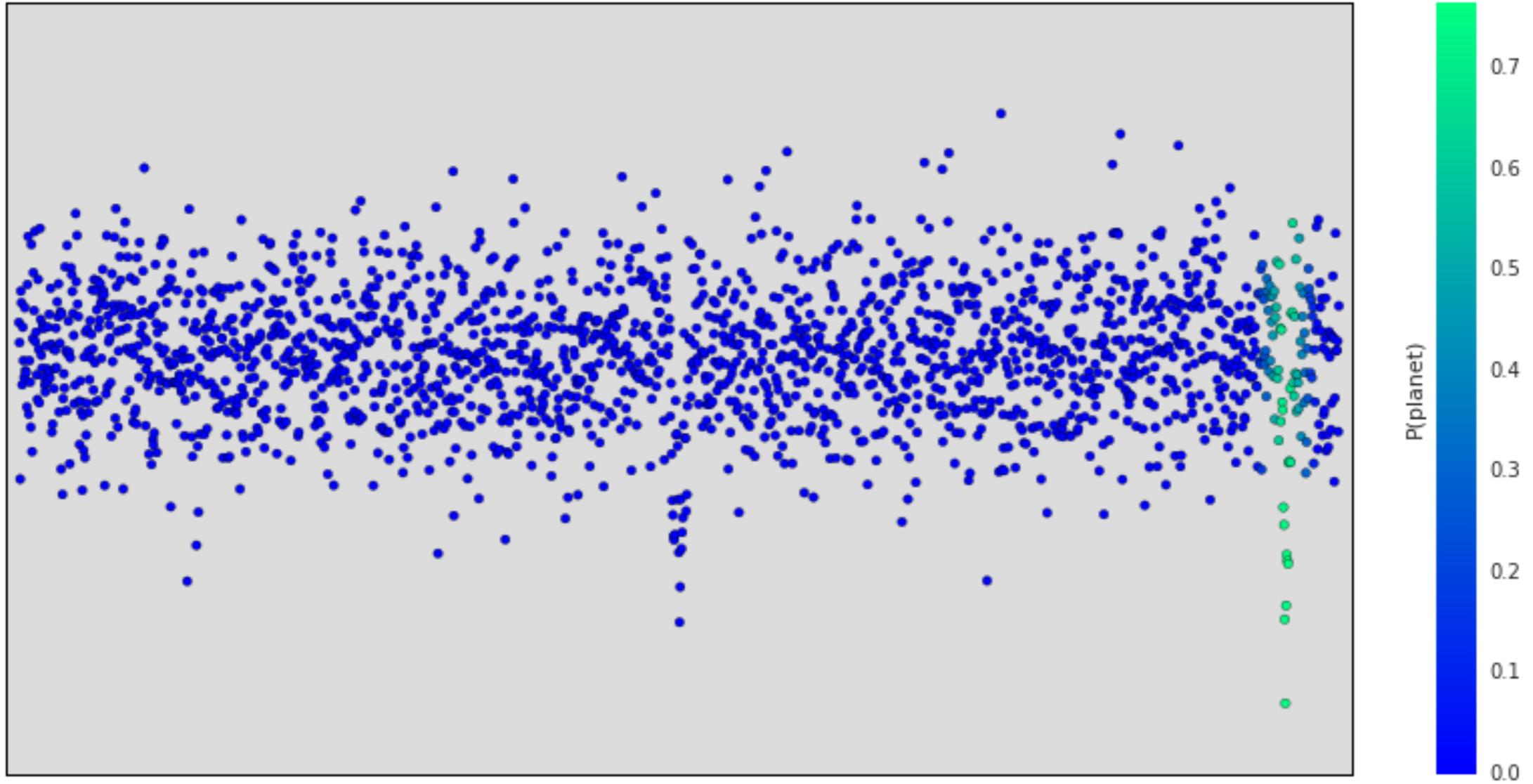
# Visualizing the Network's Decisions

TCE 3858919-2



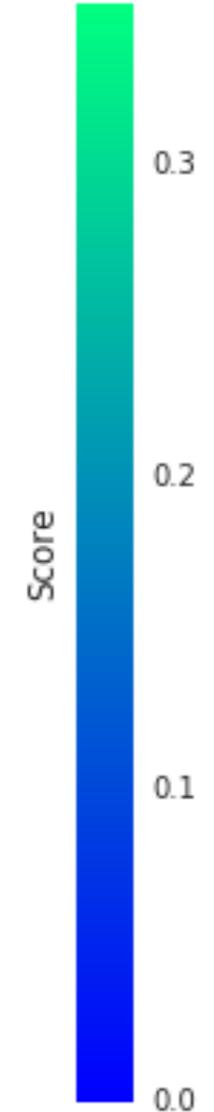
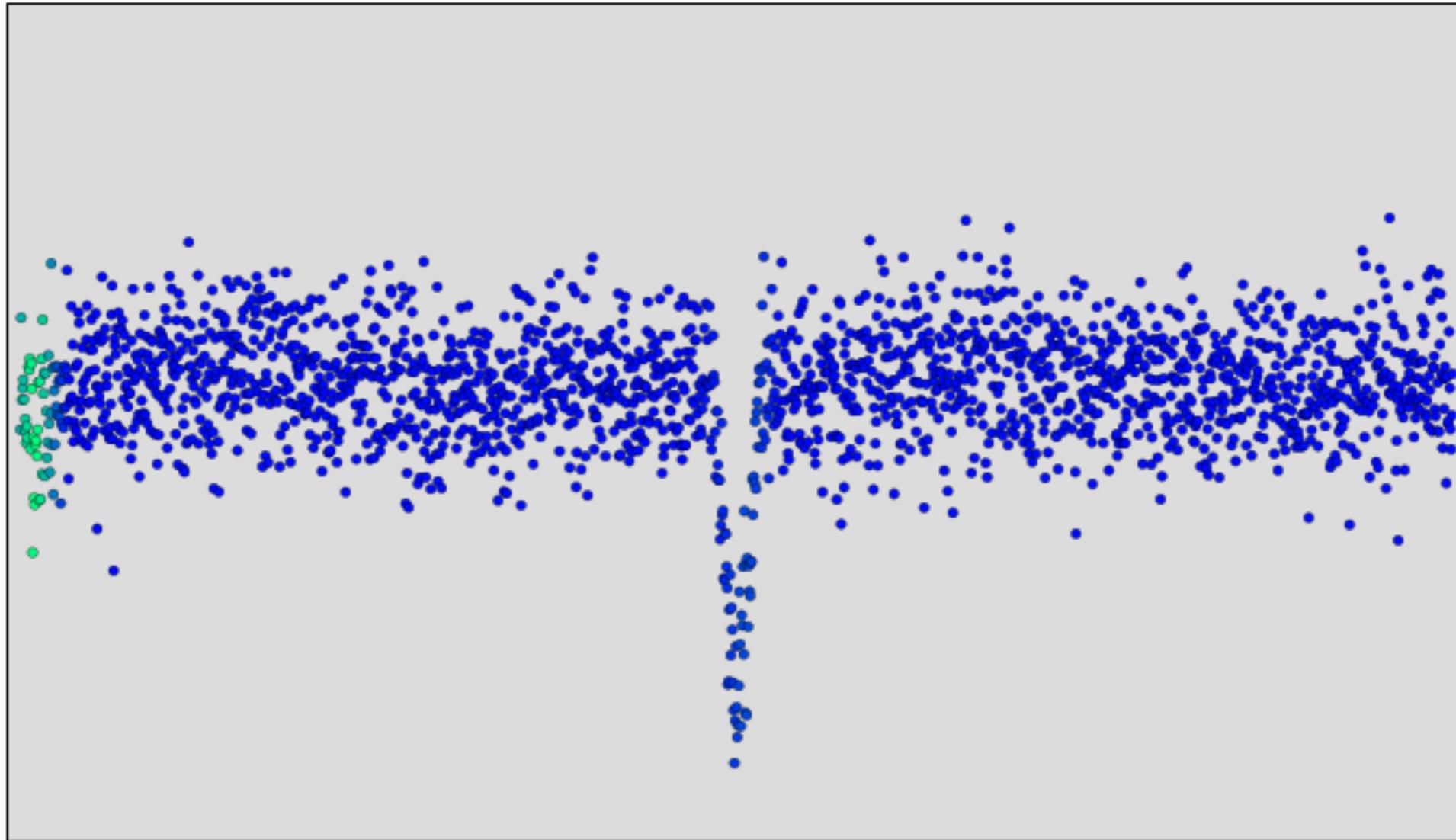
# Visualizing the Network's Decisions

TCE 4847782-1



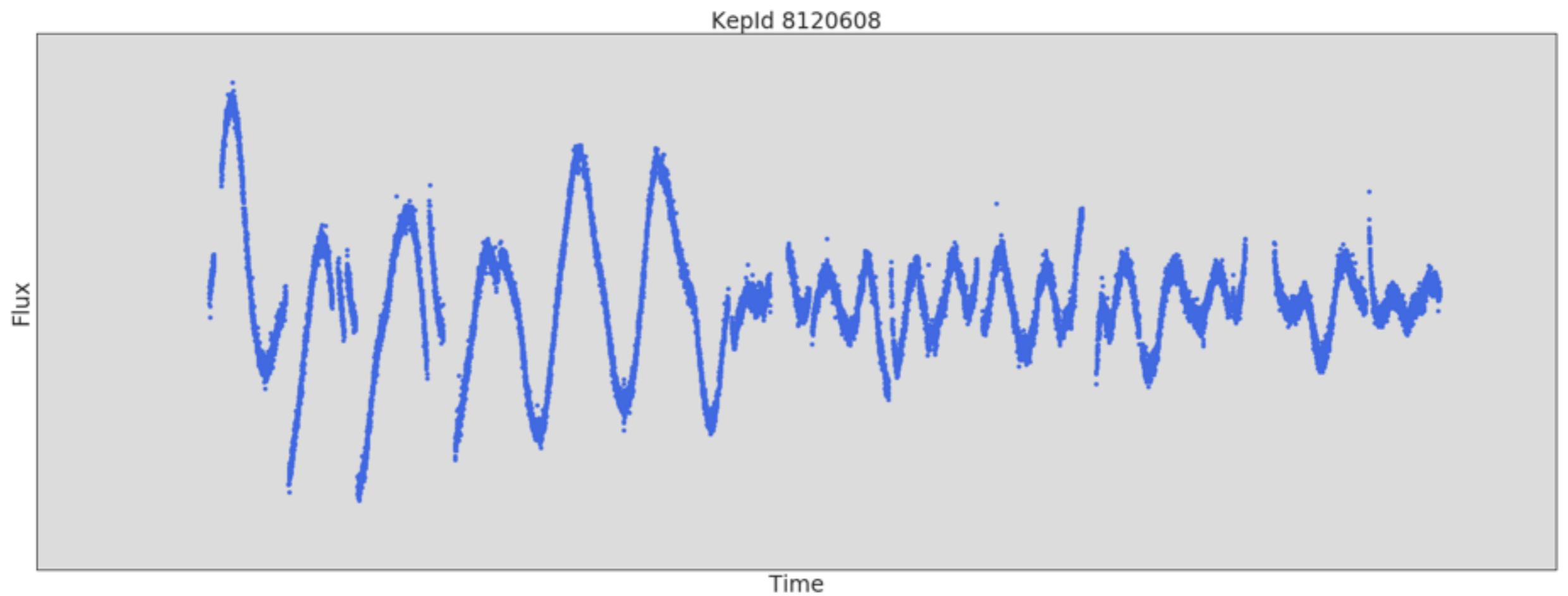
# Visualizing the Network's Decisions

TCE 8509361-1



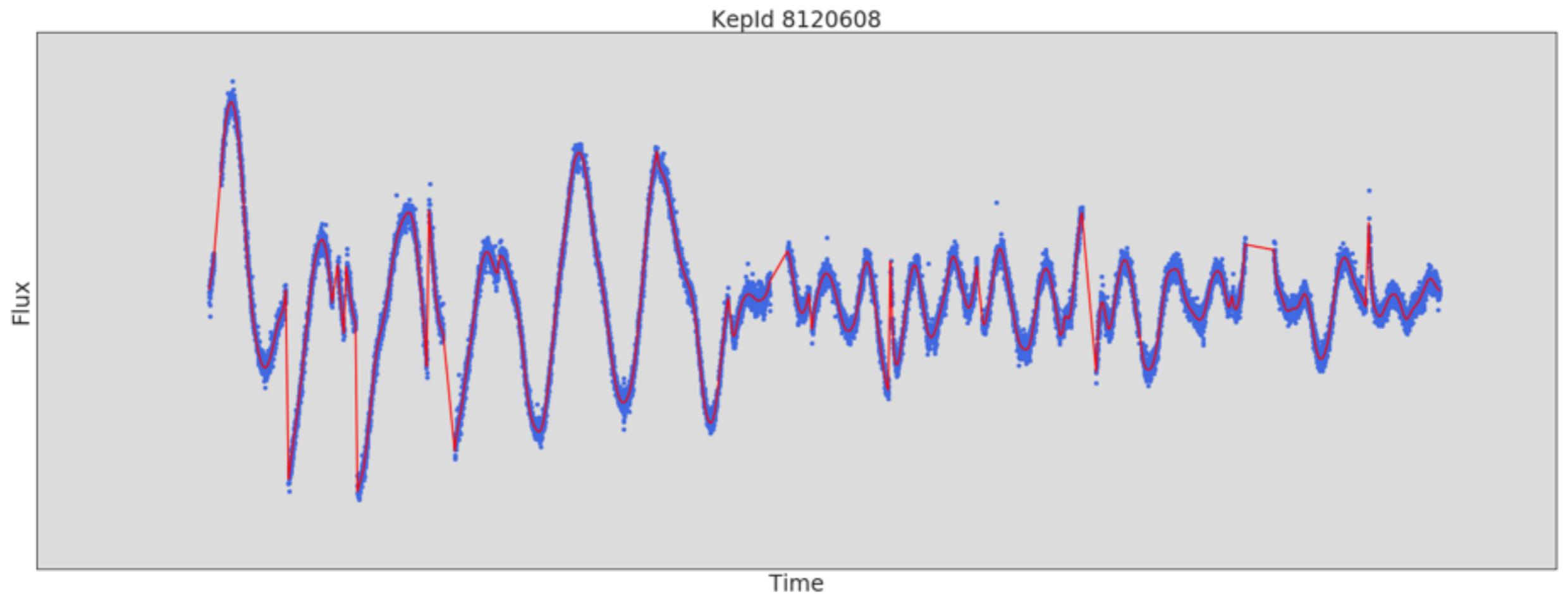
# Producing Input Vectors

Raw Light Curve



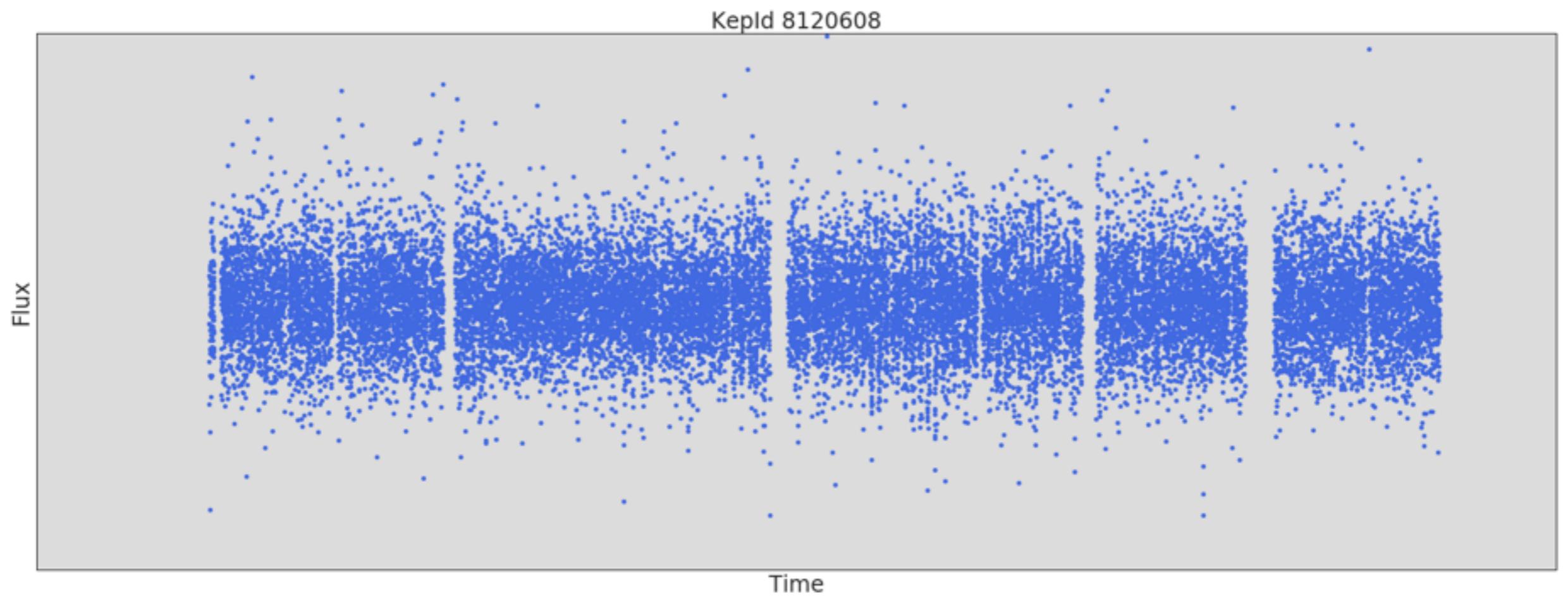
# Producing Input Vectors

Fit Normalization B-Splines



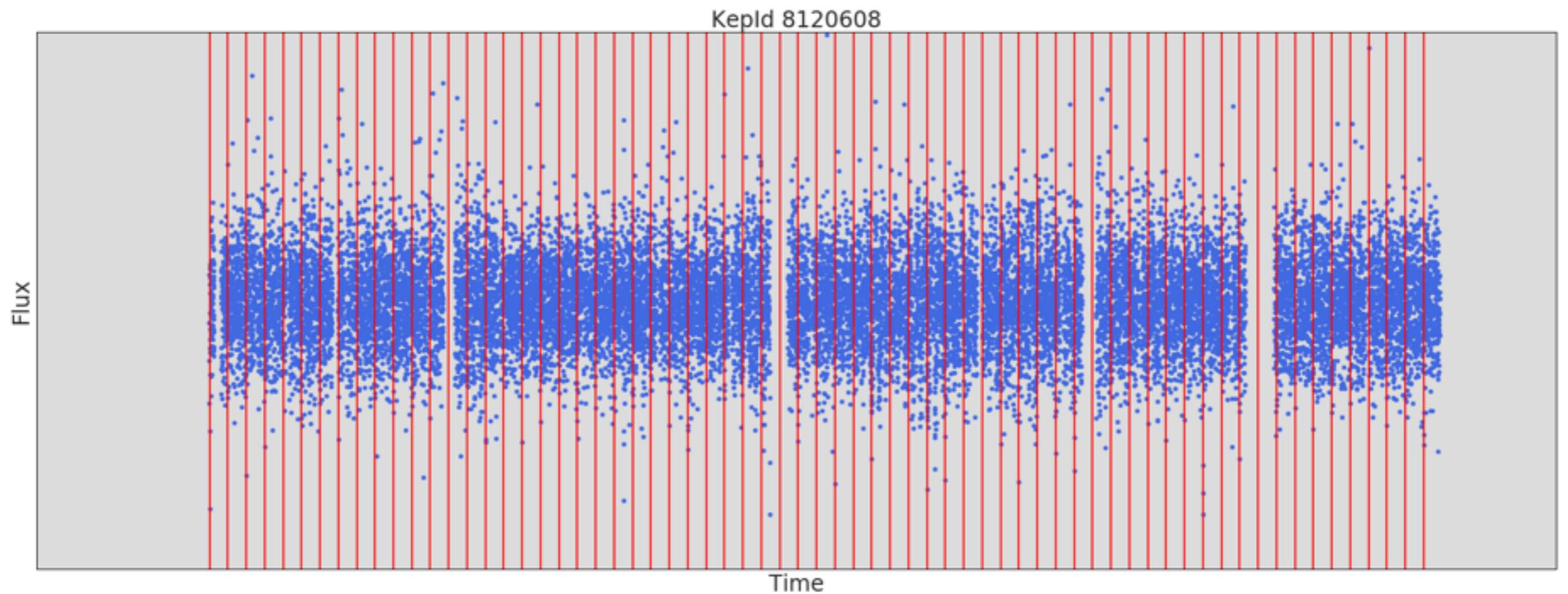
# Producing Input Vectors

Normalized Light Curve



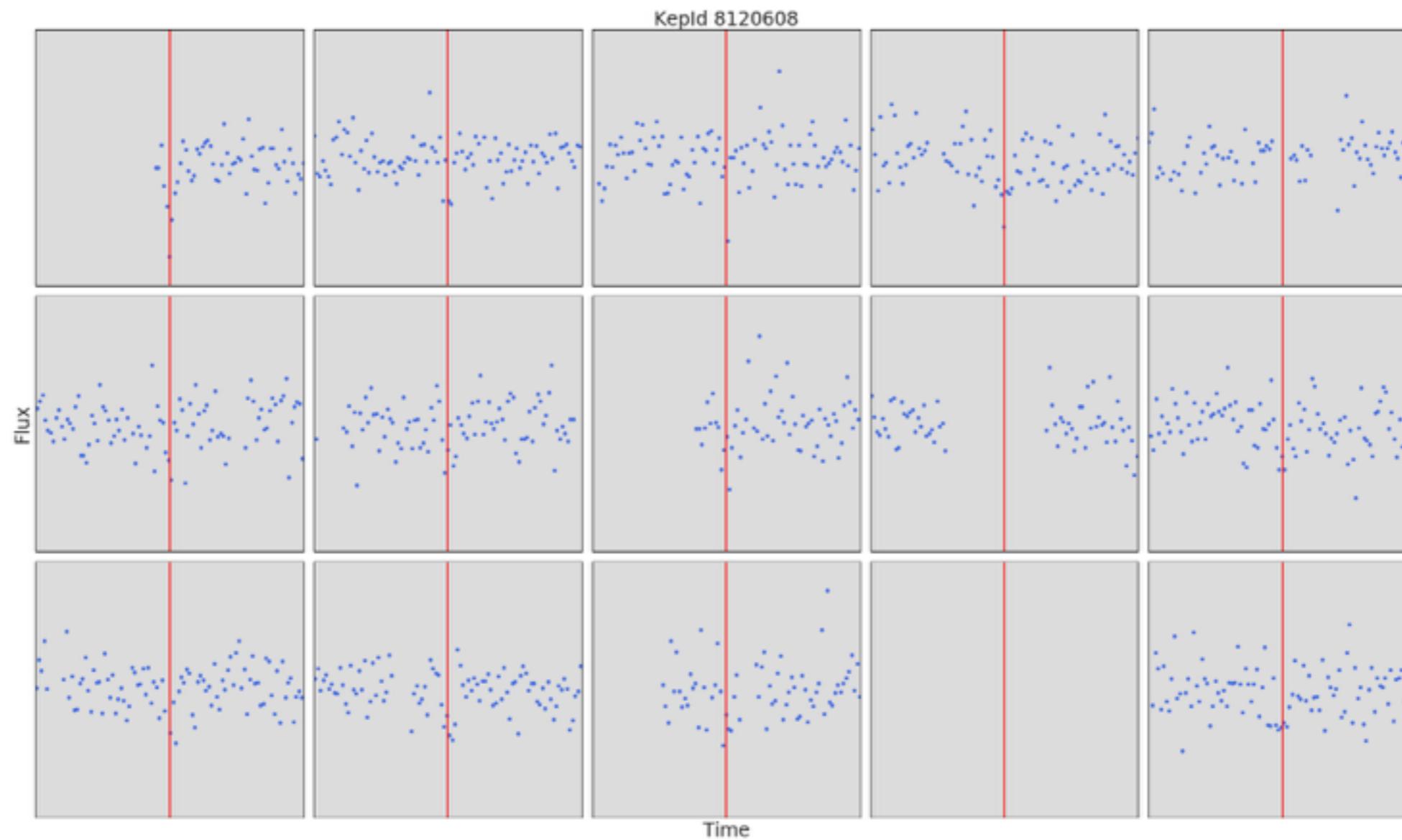
# Producing Input Vectors

Planet Transits (7 day period)



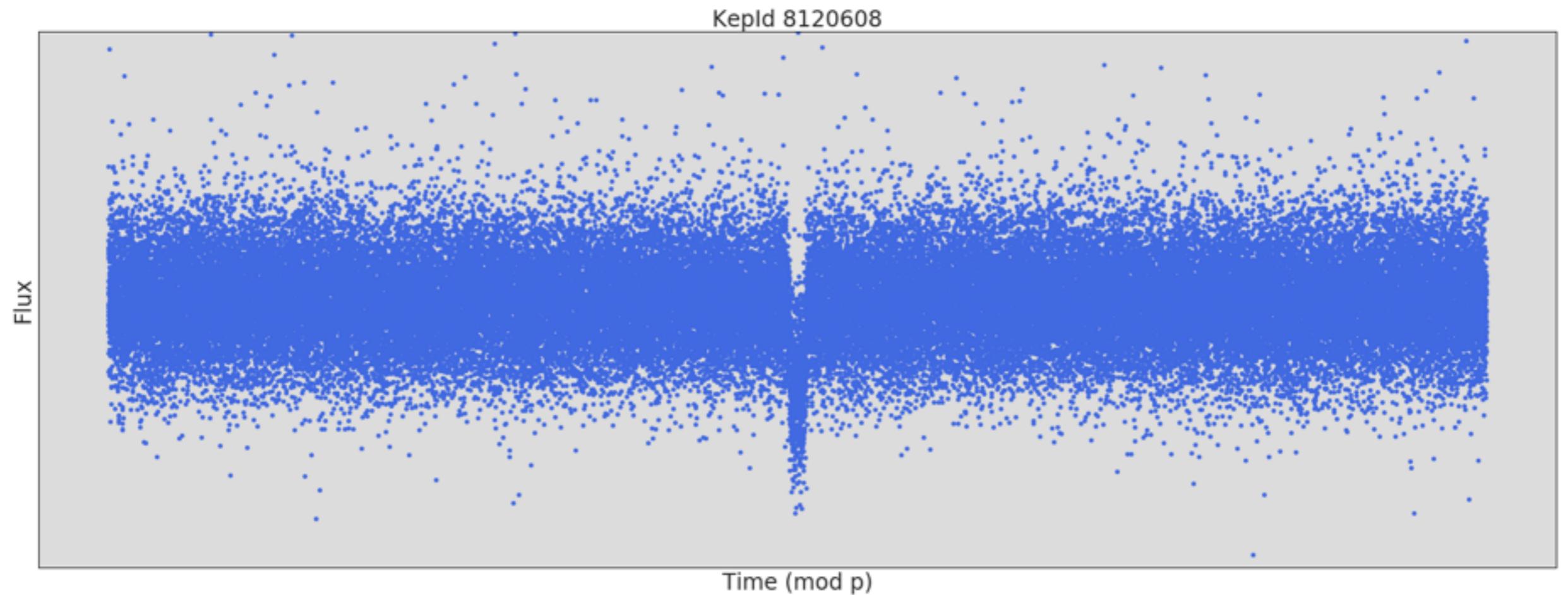
# Producing Input Vectors

## Individual Transits



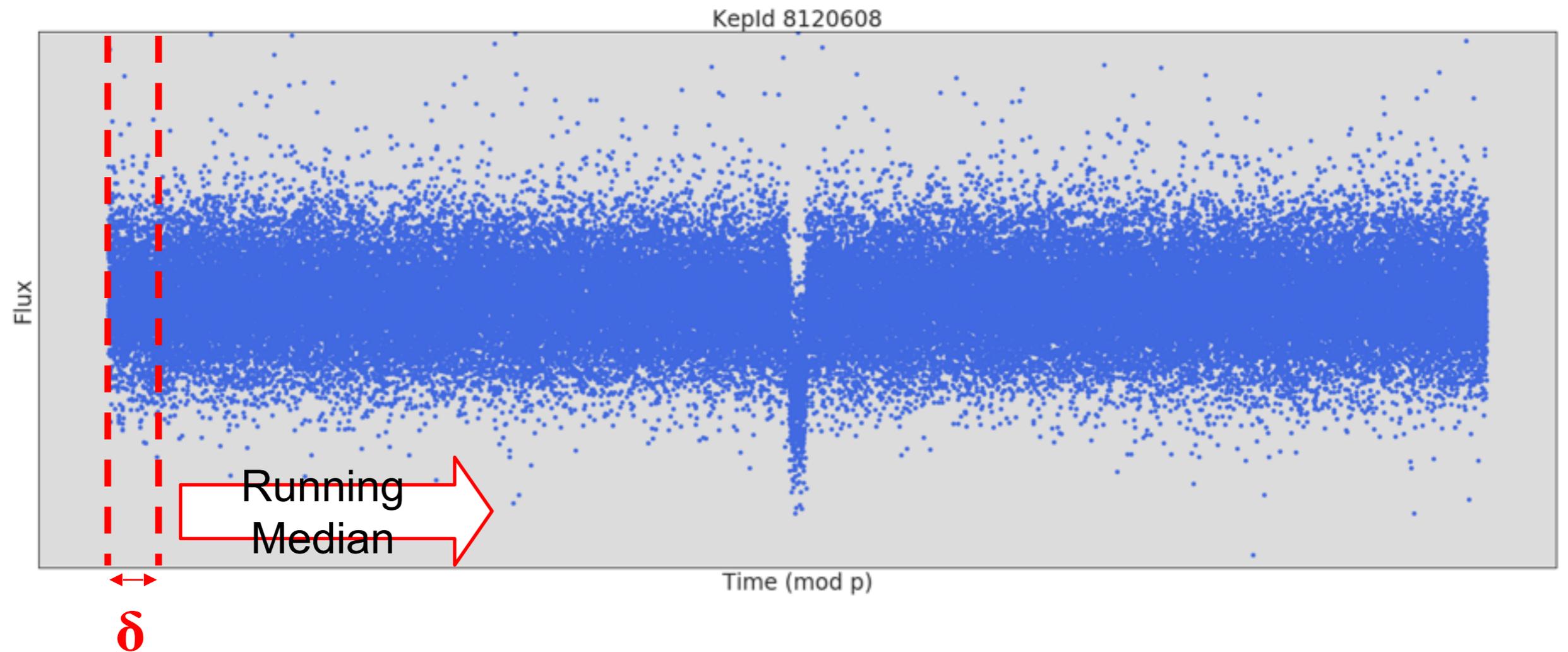
# Producing Input Vectors

Phase Folded



# Producing Input Vectors

Running Median



# Producing Input Vectors

Running Median

