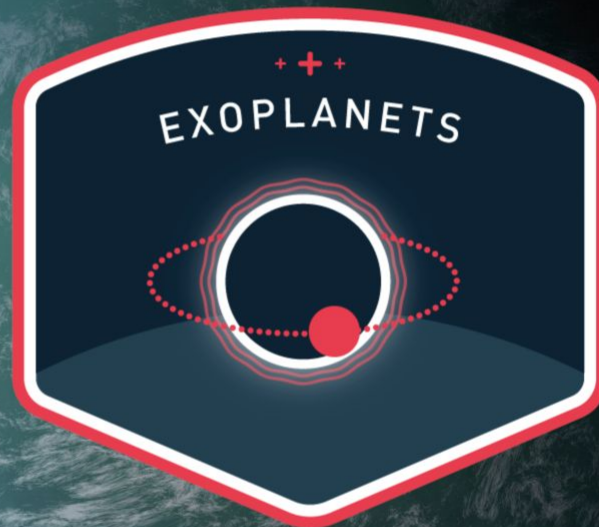


Automatic Classification of Transiting Planet Candidates with Deep Learning

Megan Ansdell¹

Hugh Osborn,² Yani Ioannou,³ Michele Sasdelli,⁴ Jeff Smith,^{5,6} Doug Caldwell,^{5,6} Chedy Raissi,⁷ Daniel Angerhausen,⁸ Jon Jenkins⁵

¹UC Berkeley, Center for Integrative Planetary Science; ²Laboratoire d'Astrophysique de Marseille; ³University of Cambridge, Machine Intelligence Lab; ⁴University of Adelaide; ⁵NASA Ames Research Center; ⁶SETI Institute; ⁷Institut National de Recherche en Informatique et en automatique; ⁸University of Bern, Center for Space & Habitability



ADASS XXVIII, College Park, 13 Nov. 2018

NASA Frontier Development Lab (FDL)

Space
Scientists

Machine Learning
Researchers

Silicon Valley
Partners

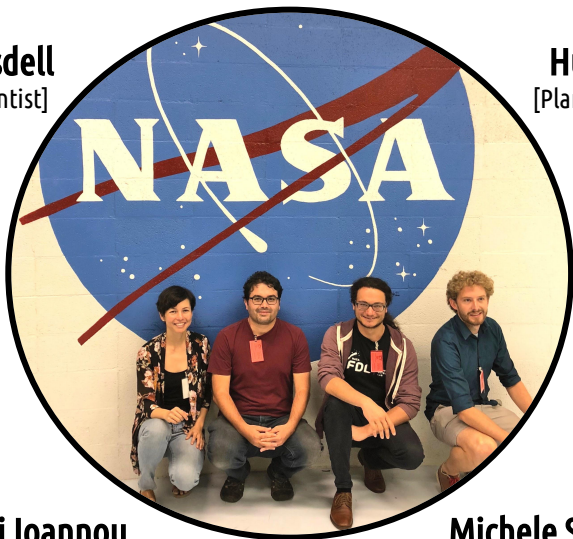


- 8 week research accelerator hosted at NASA Ames & SETI
- 9 projects across 5 areas proposed by lead mentors

Innovative Solutions to
Space Science Problems

2018 NASA FDL Exoplanet Team

Megan Ansdell
[Planetary Scientist]
UC Berkeley



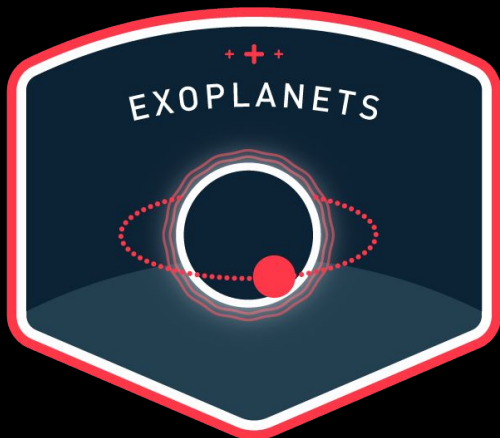
Hugh Osborn
[Planetary Scientist]
LAM, Marseille

Yani Ioannou
[Deep Learning Expert]
University of Cambridge

Michele Sasdelli
[Deep Learning Expert]
University of Adelaide

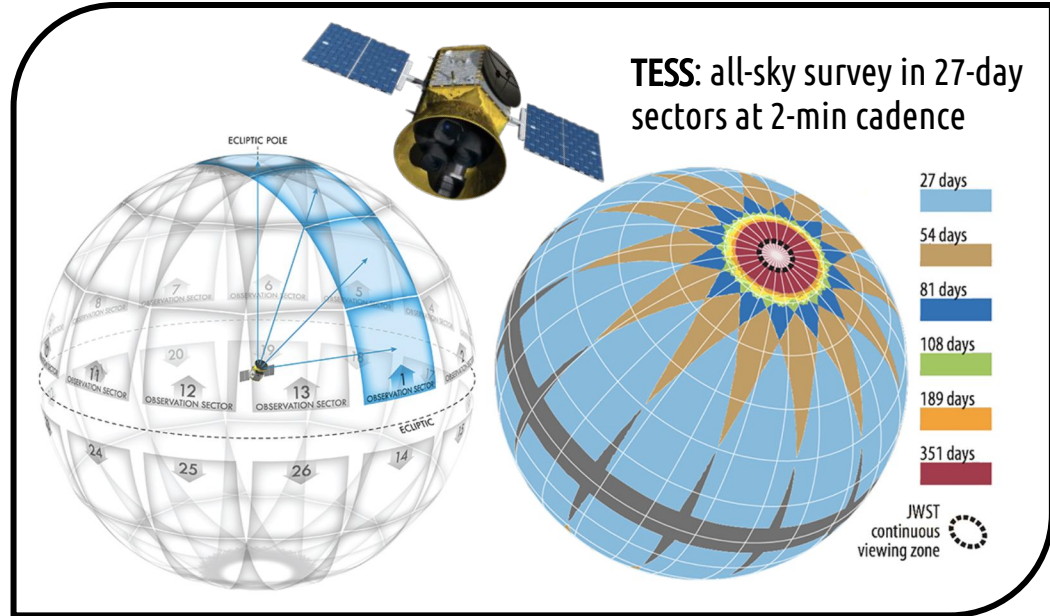
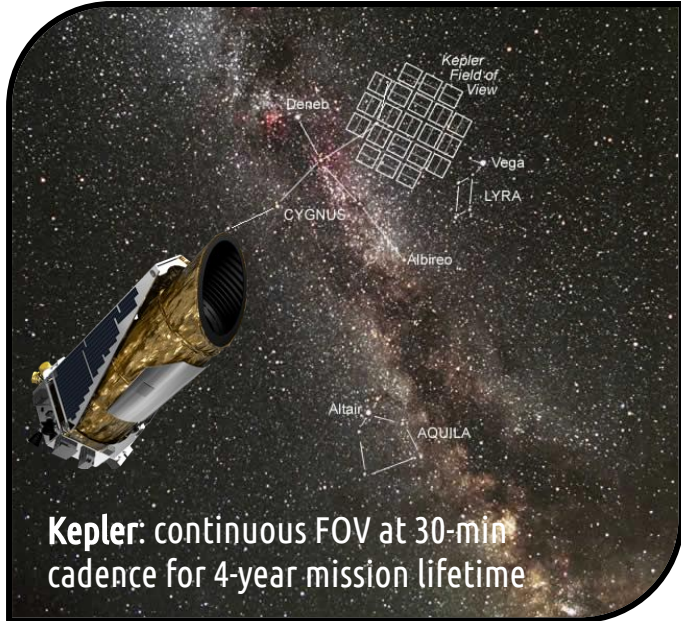
2018 FDL Exoplanet Team Mentors:

- *Science Expertise* → J. Smith, D. Caldwell, J. Jenkins (NASA Ames / SETI Institute)
Daniel Angerhausen (University of Bern / CSH)
- *Machine Learning* → C. Raïssi (INRIA),
Yarin Gal (Oxford)
- *Compute Power* → Massimo Mascaro (Google Cloud)

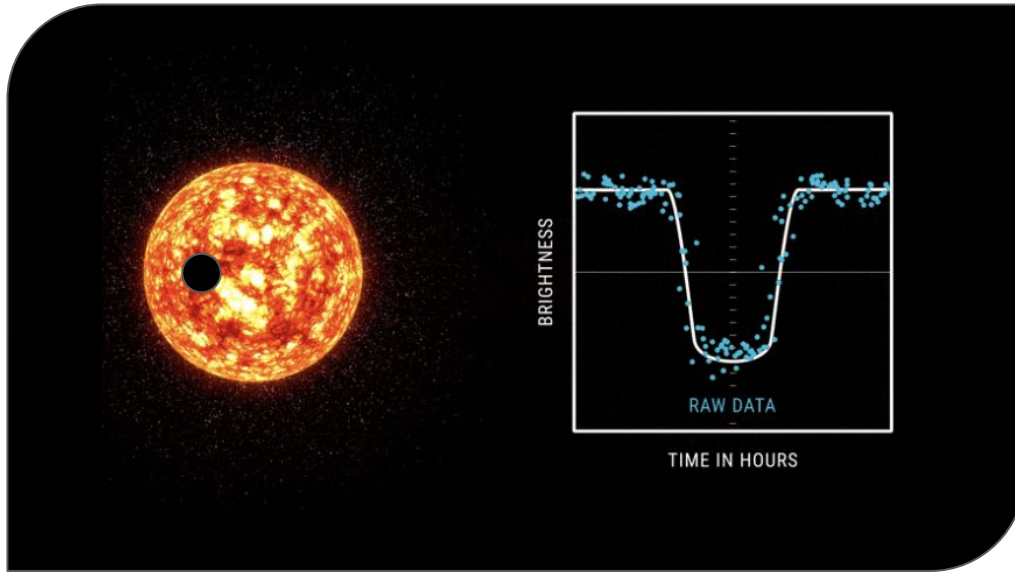


Challenge: increase the efficacy
and yield of **exoplanet transit**
detections with deep learning

The Data: Kepler & TESS Light Curves

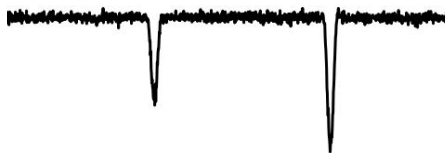
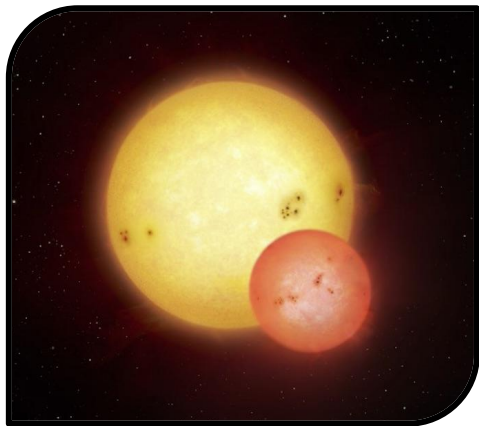


The Data: Kepler & TESS Light Curves

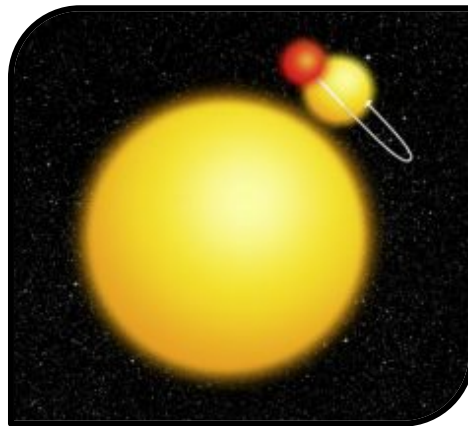


- Orbiting exoplanets transit host star
- Distinct box-shaped transit
- Very shallow 0.01%–1.0% flux dips

The Data: False Positives



Eclipsing Binaries (EBs)



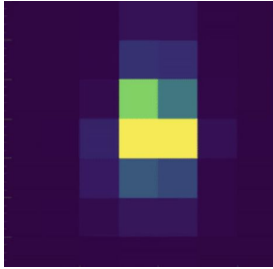
Background Eclipsing Binaries (BEBs)



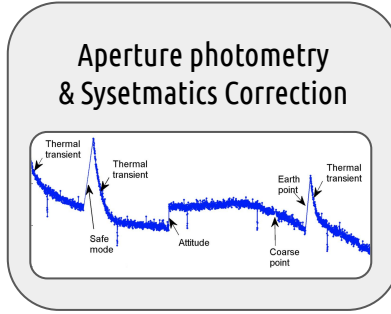
Stellar Variability / Instrumental Noise

Kepler/TESS Science Processing Pipelines

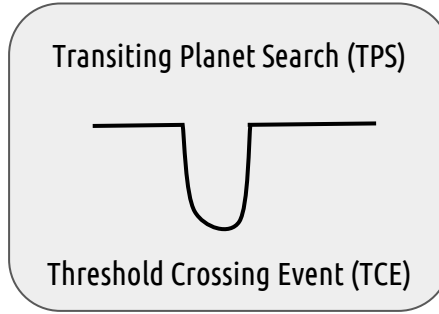
Target Pixel File (TPF)



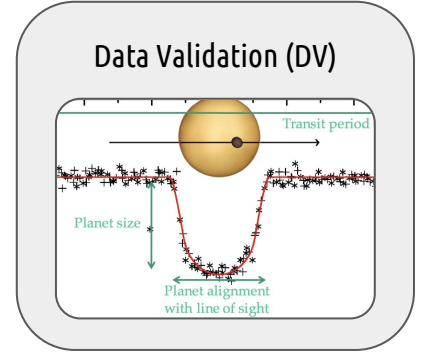
Smith+2012, Stumpe+2012



Jenkins+2010, Seader+2013



Wu+2010

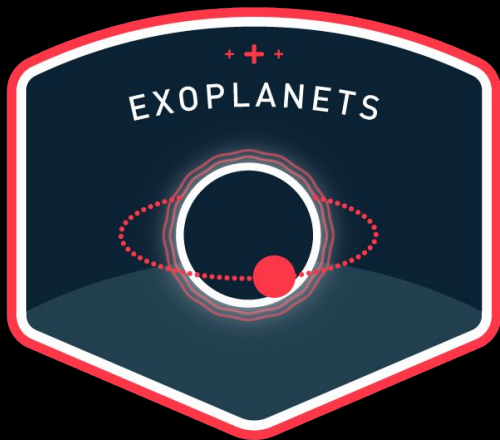


Exoplanet Catalogues

Star Name	Planet Name	Planet Size (Earth radii)	Planet Alignment (degrees)	Planet Period (days)
102040	102040 b	1.04	0.000000	13.06017
102041	102041 b	1.04	0.000000	13.06017
102042	102042 b	1.04	0.000000	13.06017
102043	102043 b	1.04	0.000000	13.06017
102044	102044 b	1.04	0.000000	13.06017
102045	102045 b	1.04	0.000000	13.06017
102046	102046 b	1.04	0.000000	13.06017
102047	102047 b	1.04	0.000000	13.06017
102048	102048 b	1.04	0.000000	13.06017
102049	102049 b	1.04	0.000000	13.06017
102050	102050 b	1.04	0.000000	13.06017
102051	102051 b	1.04	0.000000	13.06017
102052	102052 b	1.04	0.000000	13.06017
102053	102053 b	1.04	0.000000	13.06017
102054	102054 b	1.04	0.000000	13.06017
102055	102055 b	1.04	0.000000	13.06017
102056	102056 b	1.04	0.000000	13.06017
102057	102057 b	1.04	0.000000	13.06017
102058	102058 b	1.04	0.000000	13.06017
102059	102059 b	1.04	0.000000	13.06017
102060	102060 b	1.04	0.000000	13.06017
102061	102061 b	1.04	0.000000	13.06017
102062	102062 b	1.04	0.000000	13.06017
102063	102063 b	1.04	0.000000	13.06017
102064	102064 b	1.04	0.000000	13.06017
102065	102065 b	1.04	0.000000	13.06017
102066	102066 b	1.04	0.000000	13.06017
102067	102067 b	1.04	0.000000	13.06017
102068	102068 b	1.04	0.000000	13.06017
102069	102069 b	1.04	0.000000	13.06017
102070	102070 b	1.04	0.000000	13.06017
102071	102071 b	1.04	0.000000	13.06017
102072	102072 b	1.04	0.000000	13.06017
102073	102073 b	1.04	0.000000	13.06017
102074	102074 b	1.04	0.000000	13.06017
102075	102075 b	1.04	0.000000	13.06017
102076	102076 b	1.04	0.000000	13.06017
102077	102077 b	1.04	0.000000	13.06017
102078	102078 b	1.04	0.000000	13.06017
102079	102079 b	1.04	0.000000	13.06017
102080	102080 b	1.04	0.000000	13.06017
102081	102081 b	1.04	0.000000	13.06017
102082	102082 b	1.04	0.000000	13.06017
102083	102083 b	1.04	0.000000	13.06017
102084	102084 b	1.04	0.000000	13.06017
102085	102085 b	1.04	0.000000	13.06017
102086	102086 b	1.04	0.000000	13.06017
102087	102087 b	1.04	0.000000	13.06017
102088	102088 b	1.04	0.000000	13.06017
102089	102089 b	1.04	0.000000	13.06017
102090	102090 b	1.04	0.000000	13.06017
102091	102091 b	1.04	0.000000	13.06017
102092	102092 b	1.04	0.000000	13.06017
102093	102093 b	1.04	0.000000	13.06017
102094	102094 b	1.04	0.000000	13.06017
102095	102095 b	1.04	0.000000	13.06017
102096	102096 b	1.04	0.000000	13.06017
102097	102097 b	1.04	0.000000	13.06017
102098	102098 b	1.04	0.000000	13.06017
102099	102099 b	1.04	0.000000	13.06017
102100	102100 b	1.04	0.000000	13.06017

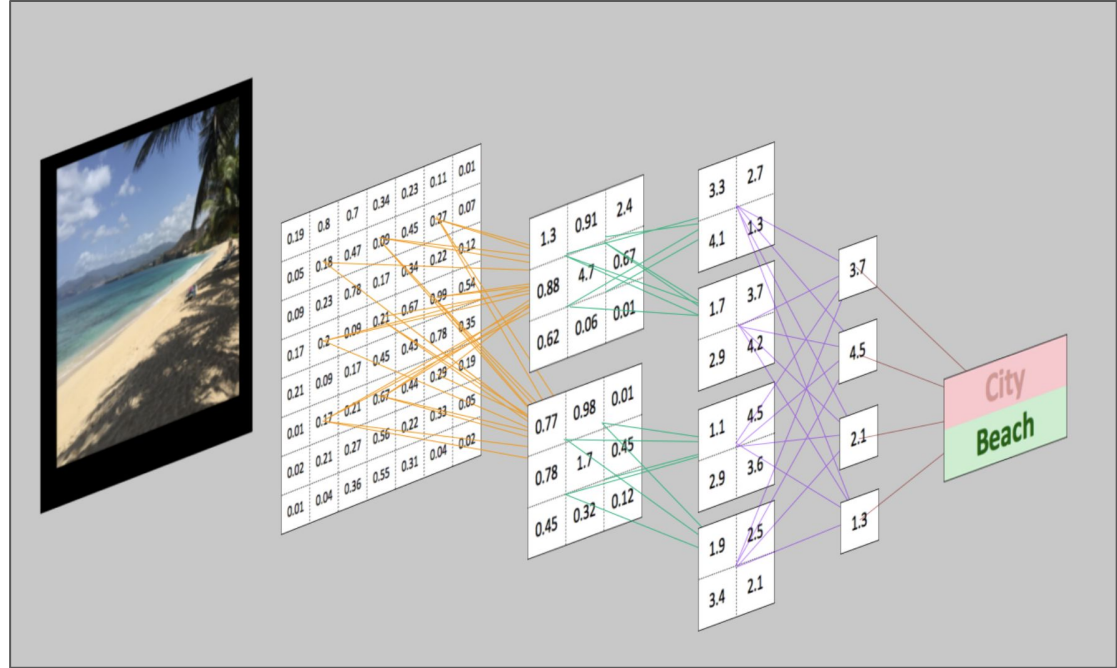
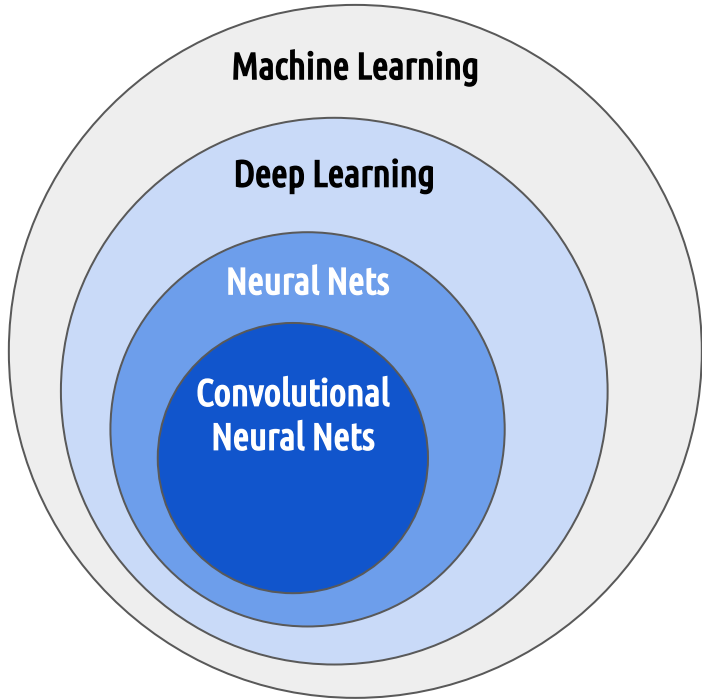
Batalha+2013, Burke+2014, Rowe+2015, Mullally+2015





**Challenge: increase the efficacy
and yield of exoplanet transit
detections with **deep learning****

Classifying Transits with Deep Learning



Classifying Transits with Deep Learning

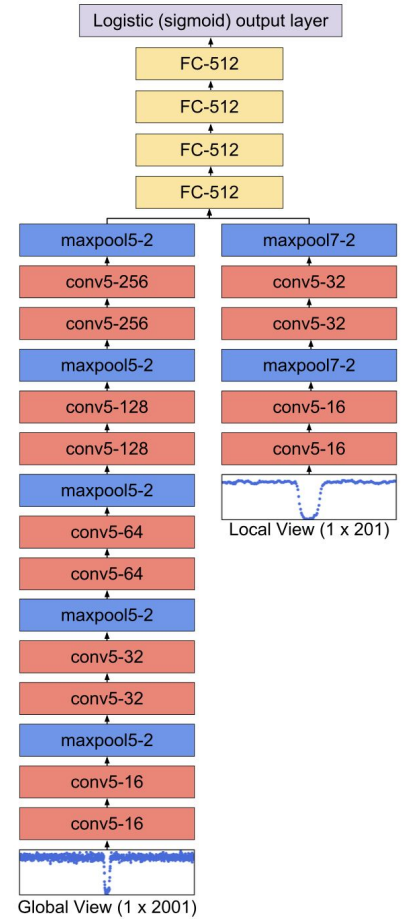
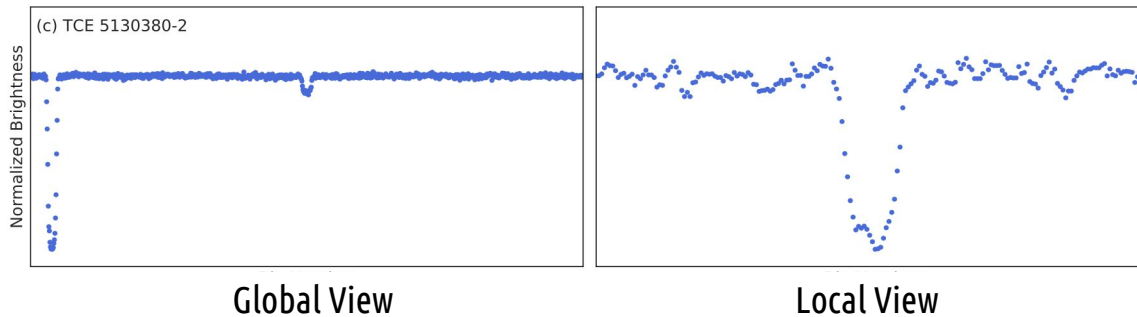
- **Quick** → trained models take seconds/minutes to apply to new data
- **Systematic** → important for calculating exoplanet occurrence rates
- **Upgradable** → re-doing analysis with upgrades is easy/quick
- **Quantifiable** → can assign probabilities/uncertainties to planet candidates

Classifying Transits with Deep Learning

Astronet

Shallue & Vanderburg (2018)

- Deep Convolutional Neural Net written in TensorFlow
- Inputs are “local” and “global” transit view of each TCE
- Two disjoint 1D convolutional columns + 4 fully connected layers
- Output is binary classifier in the range $[0,1]$



Classifying Transits with Deep Learning

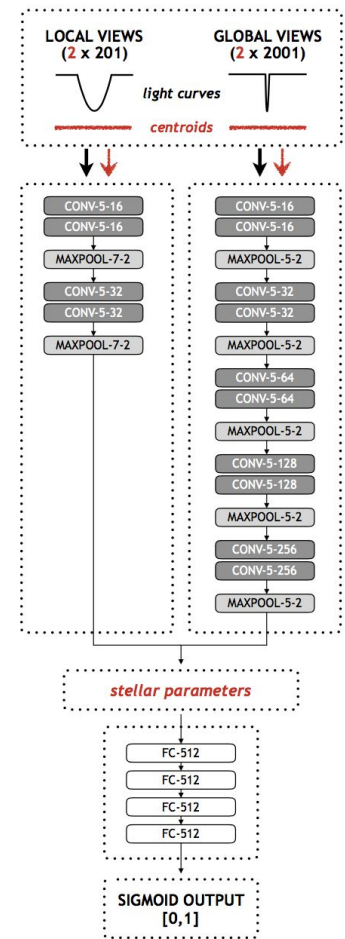
Exonet [Astronet + Scientific Domain Knowledge]

Andsell, Ioannou, Osborn, Sasdelli, et al. (2018)

- Re-implemented Astronet in PyTorch
- Added “scientific domain knowledge” to architecture + inputs
- Improved overall model performance by ~1-3%
- 15-20% higher recall for lowest SNR transits (Earth-sized planets)

arXiv: 1810.13434

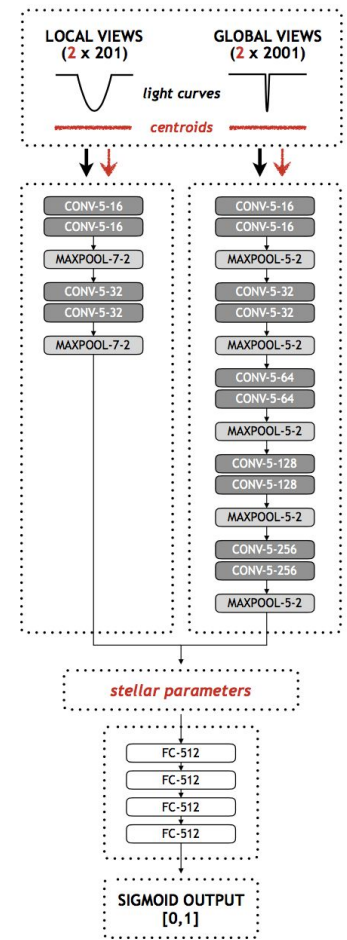
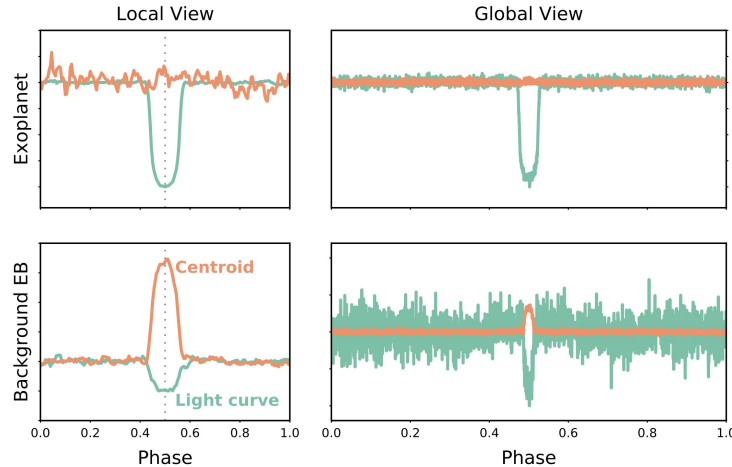
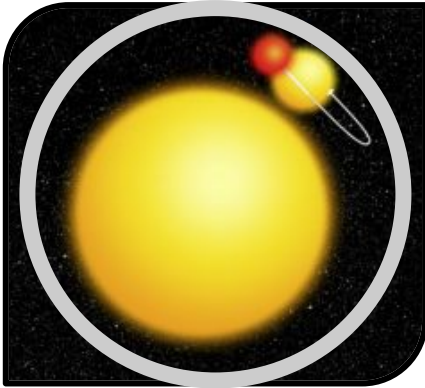
<https://gitlab.com/frontierdevelopmentlab/exoplanets>



Scientific Domain Knowledge

Centroid Time-series

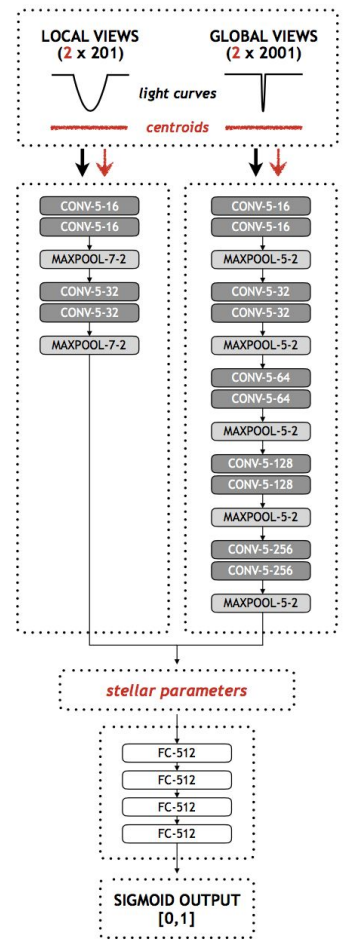
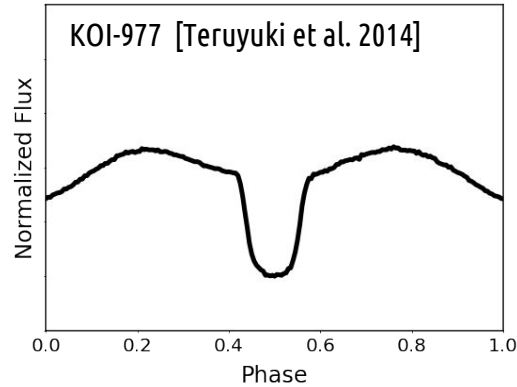
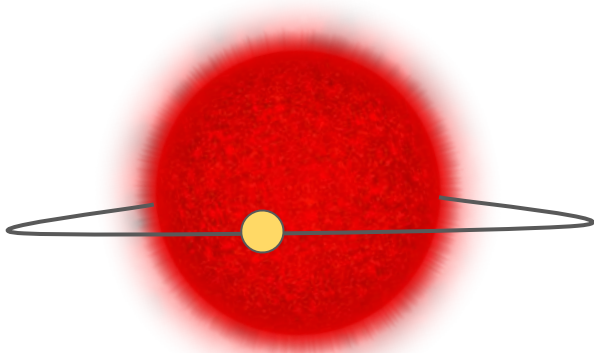
- Position of center of light in TPF as function of time
- Important for identifying EBs and BEBs



Scientific Domain Knowledge

Stellar Properties

- From KOI catalog: mass, radius, density, surface gravity, metallicity
- Important for identifying, e.g., giant star eclipsing binaries

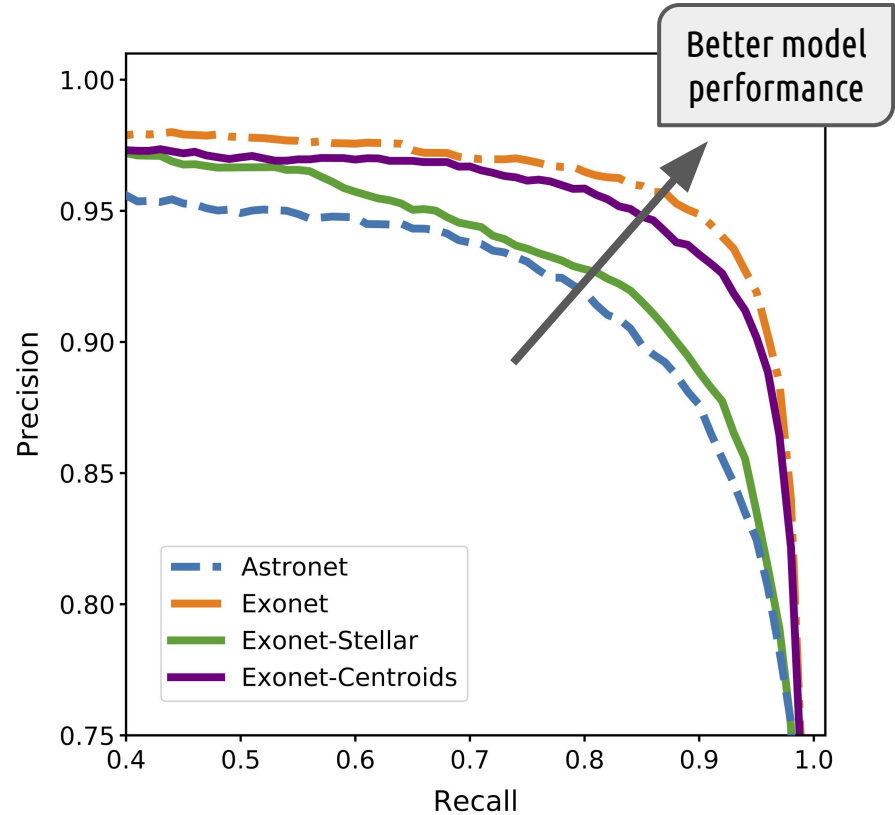


Scientific Domain Knowledge

Improved Overall Performance

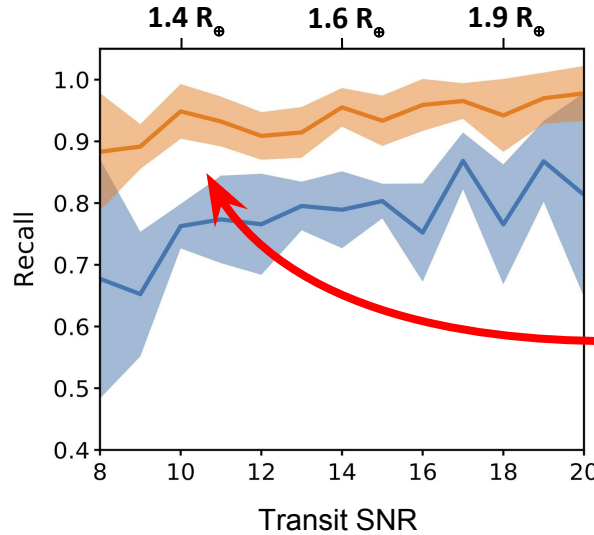
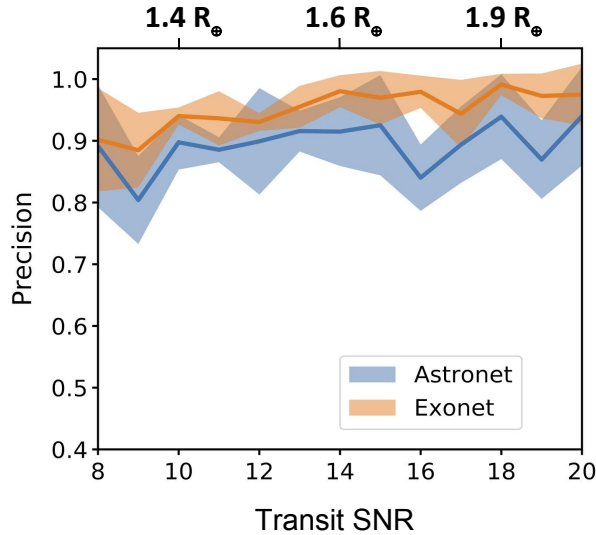
	Accuracy	Avg. Precision
Astronet	95.8%	95.5%
Exonet	97.5%	98.0%

- Accuracy = % of correct classifications
- Precision = % of classified planets that are true planets
- Recall = % of planets recovered by model



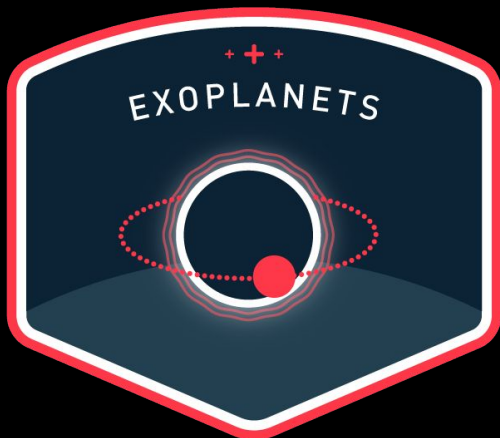
Scientific Domain Knowledge

Improved Performance for Lowest SNR Transits



Future missions like TESS & PLATO will focus on small planets

15-20% gains in recall for Earth-sized planets



**Scientific domain knowledge
improves exoplanet transit
classification with deep learning**

Questions?

arXiv: 1810.13434

gitlab.com/frontierdevelopmentlab/exoplanets

Megan Ansdell, CIPS Postdoctoral Fellow, UC Berkeley
ADASS XXVIII, College Park, 13 Nov. 2018