CSH, Bern, 28/03/2019

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Classification of exoplanet candidates in the era of Deep Neural Networks

Hugh Osborn

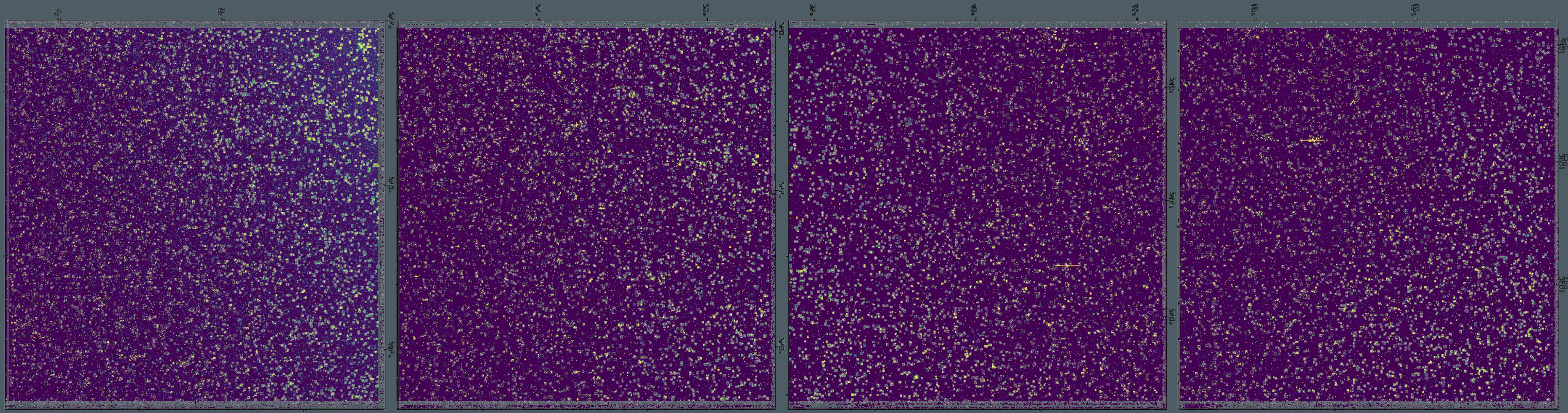
\+ Megan Ansdell, Yani Ioannou, Michele Sasdelli, Jeff Smith, Jon Jenkins, Doug Cauldwell, Chedy Raissi, Dan Angerhausen,

@exohugh

Talk Structure

- The problem of classifying exoplanet candidates from space-based transit surveys
- General Overview of Machine Learning & Neural Networks and their use in exoplanet Astronomy
- Our project on Kepler and TESS

The problem:
From raw data to planets



“Postage stamps” for target stars

Typical TESS Raw data

Kepler/TESS pipeline

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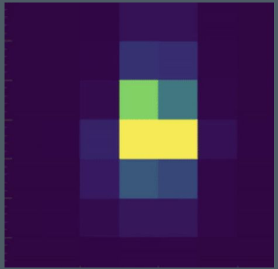
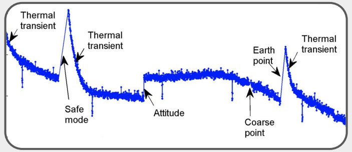
Wu+2010

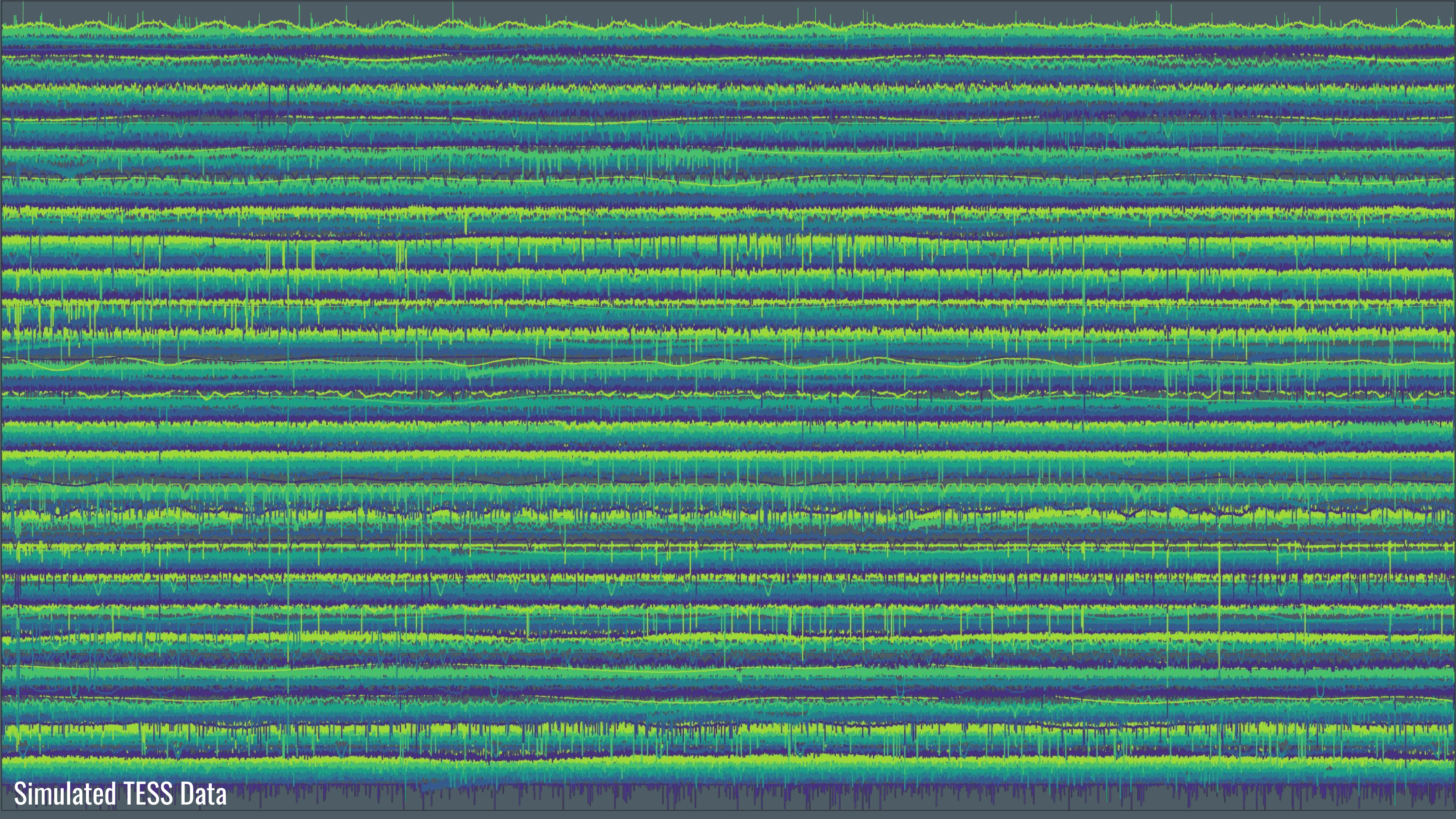
Target Pixel File (TPF)



Smith+2012, Stumpe+2012

Aperture Photometry
& Systematics Correction




Simulated TESS Data

Kepler/TESS pipeline

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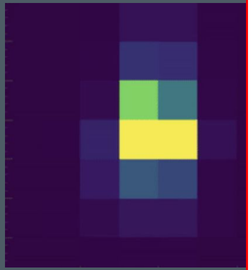
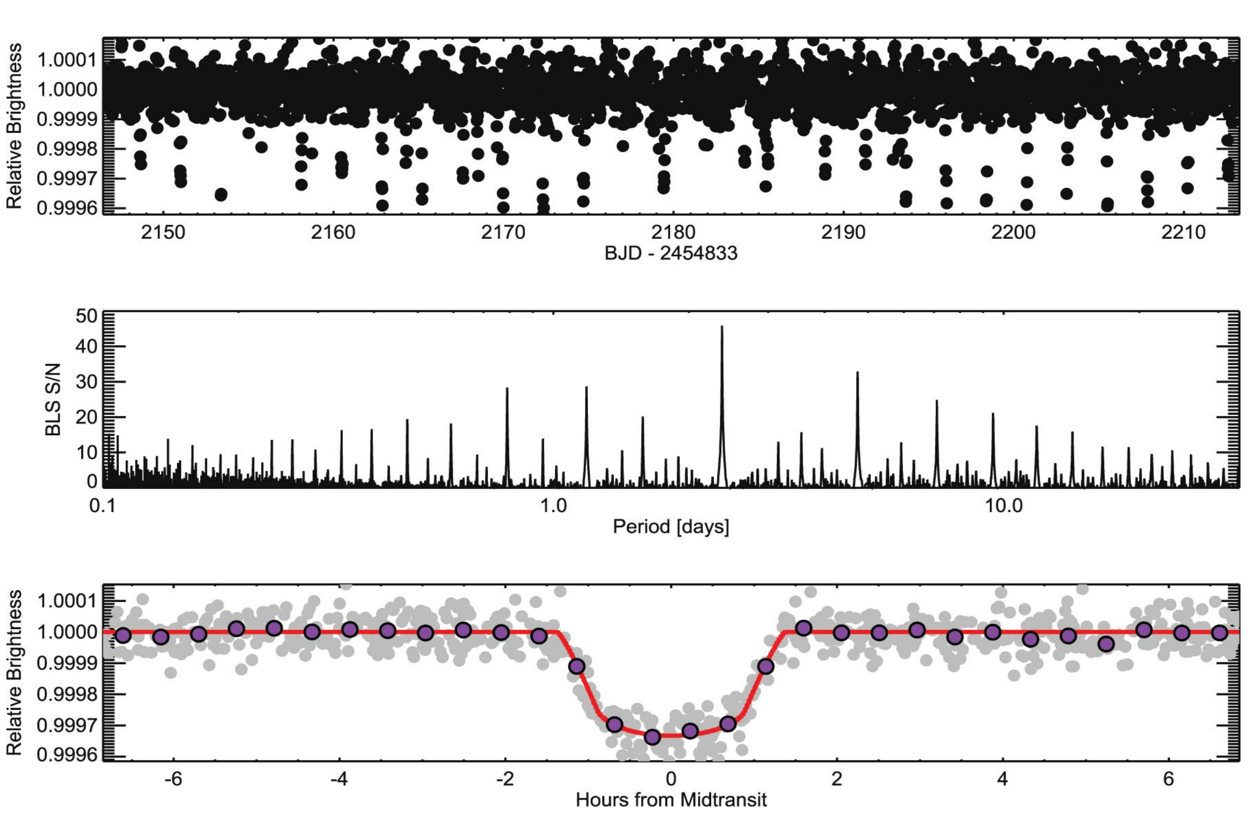
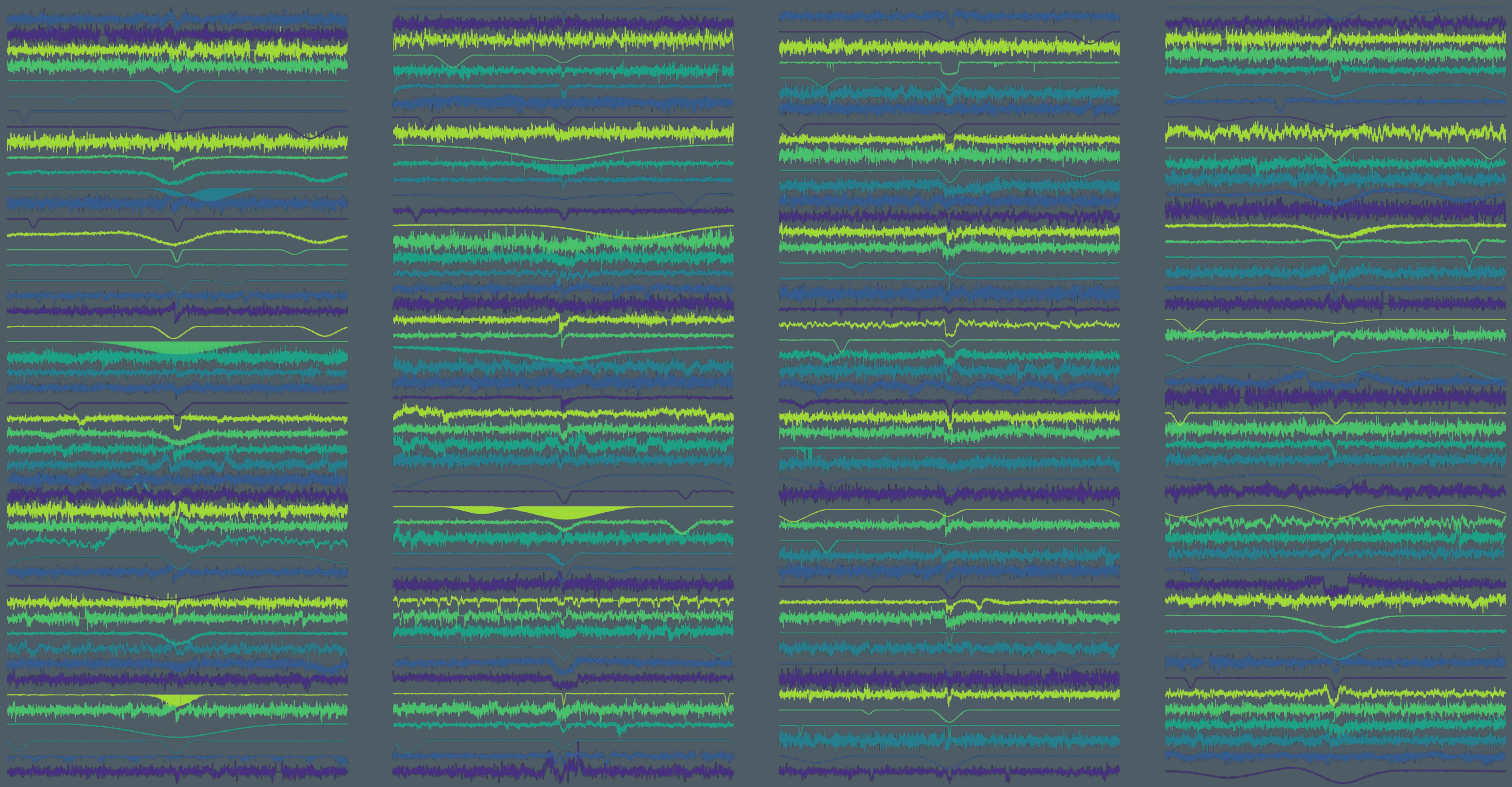
Target Pixel File (TPF)







Kepler/TESS pipeline

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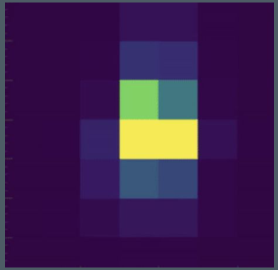
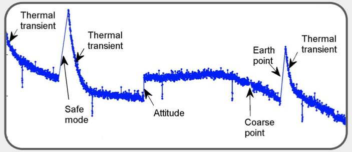


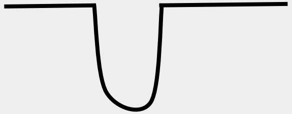
Smith+2012, Stumpe+2012

Aperture Photometry & Systematics Correction



Jenkins+2010, Seader+2013

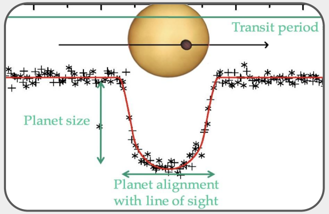
Transiting Planet Search (TPS)



Threshold Crossing Event (TCE)

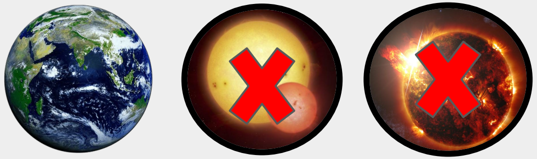
Wu+2010

Data Validation (DV)



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

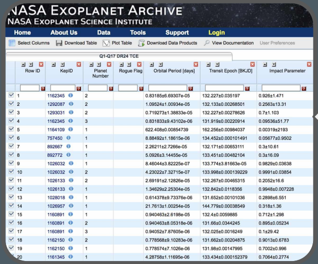
Candidate Classification
In Kepler: TCE Review Team [human vetting]



Follow-up observations

Confirm (or statistically validate) planets

Exoplanet Catalogues



Manual vetting

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Used for Kepler on all Quarters (later used as labels for machine learning)

Current TESS team: 21 vetters. >200 human hours per sector

Manual vetting

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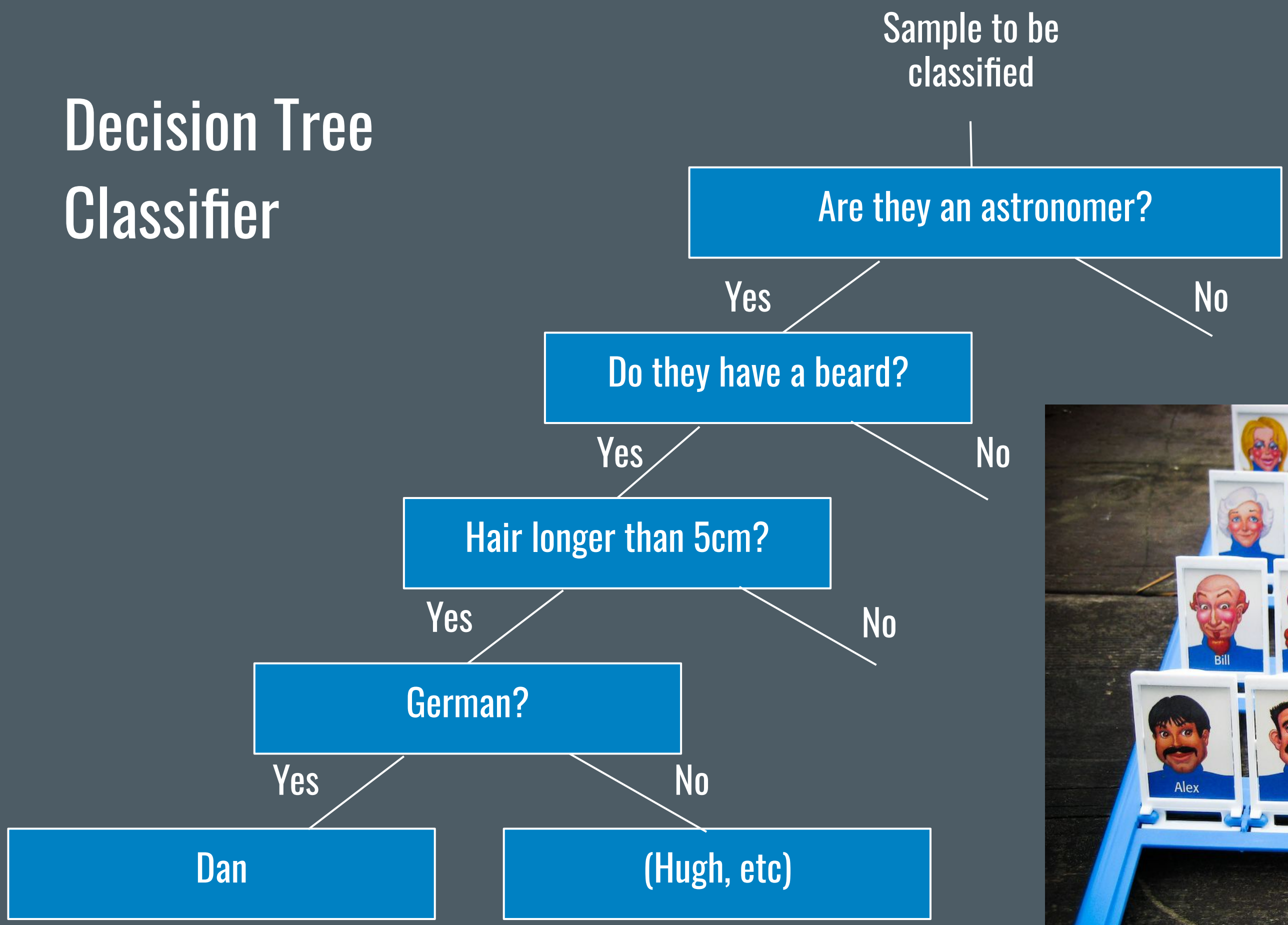
Can a machine do better?

Classification with Machine Learning


Classes >
Samples ^
< Ground truth
Bill
Claire
Frans
Alfred
Herman
Maria
Alex
Max
Anne
Philip
Tom
Richard
Robert

Decision Tree Classifier



^ Predicted class

Decision Tree Classifier

Sample to be classified

Does it have a secondary eclipse

Yes

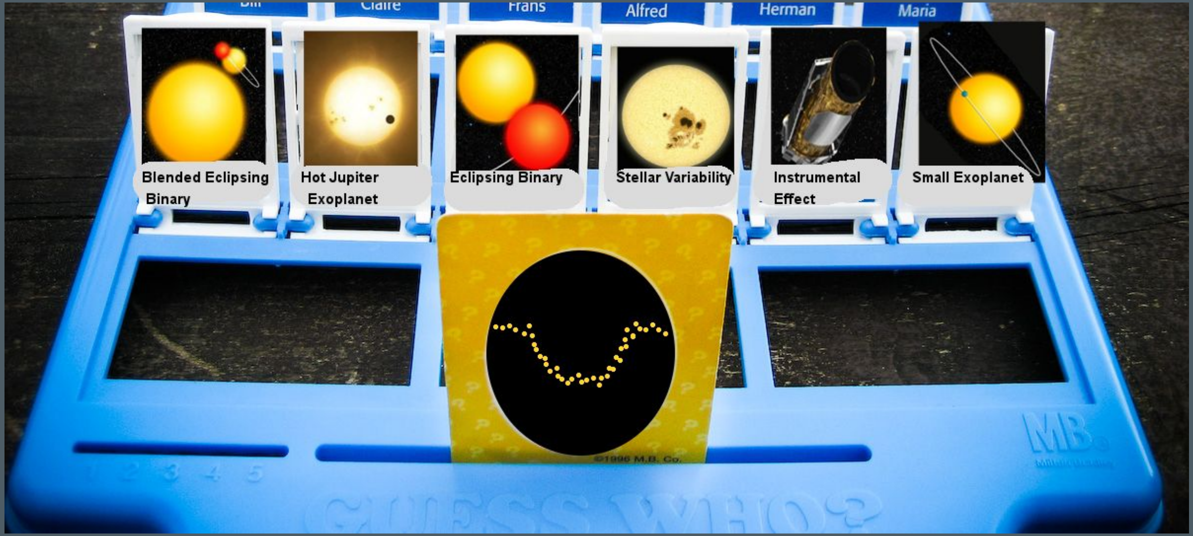
No

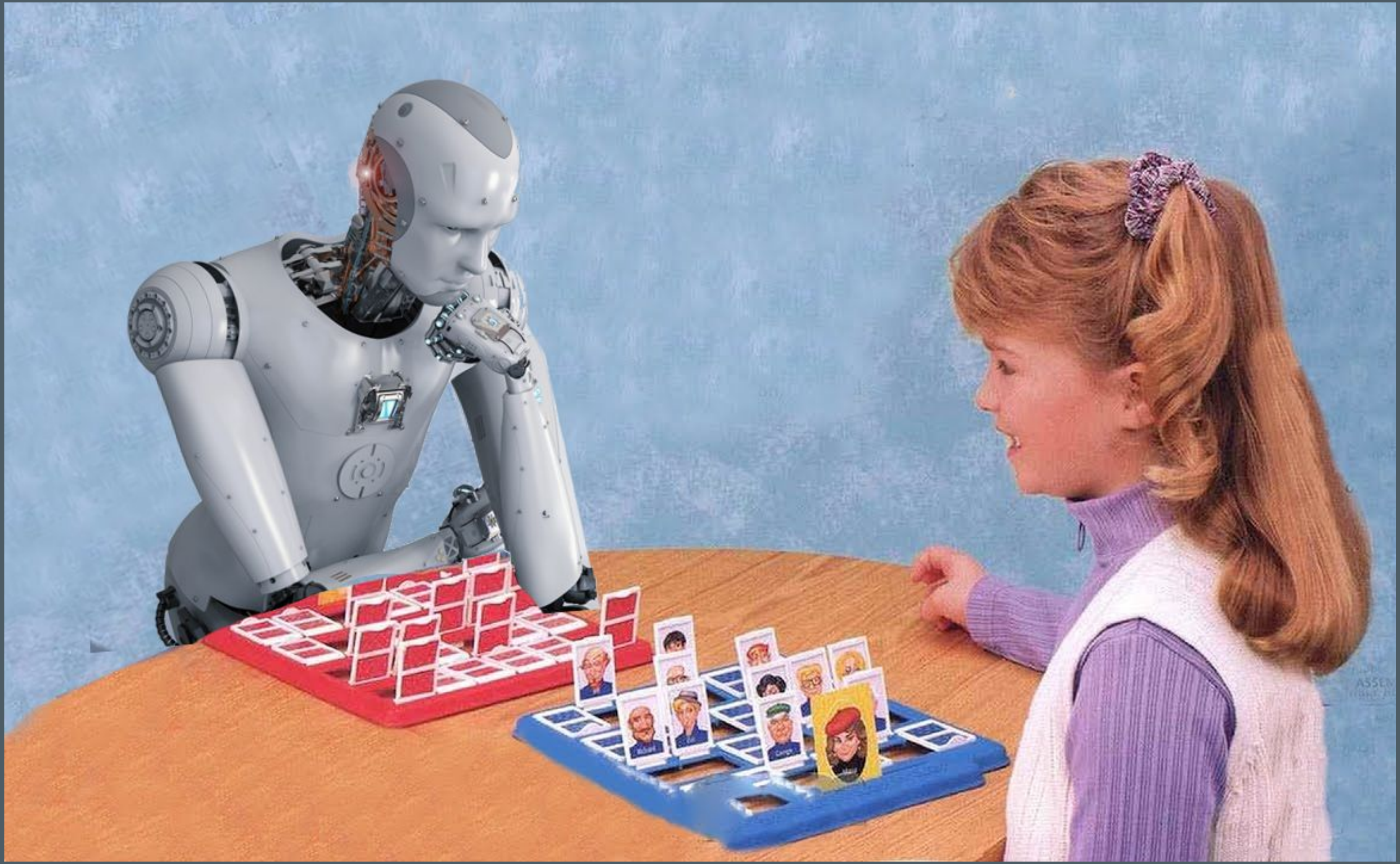
Is the modelled albedo >1

Yes

No

Eclipsing Binary





How can we classify with minimal human processing?
With Machine Learning

Machine Learning

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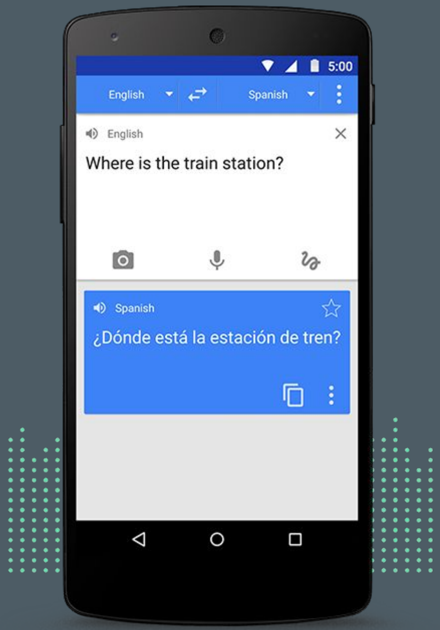
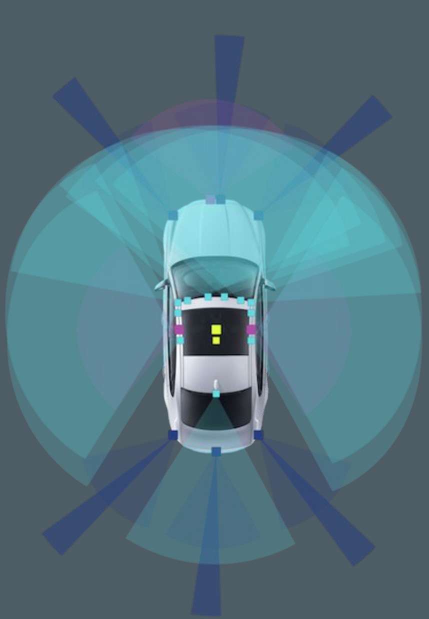


Translation



Self-driving cars

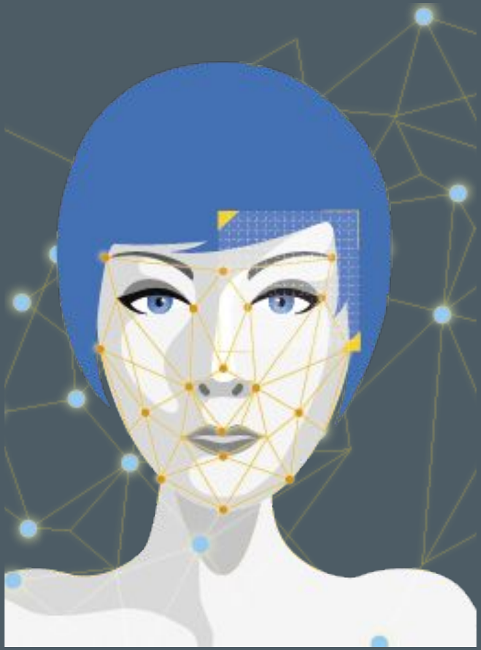
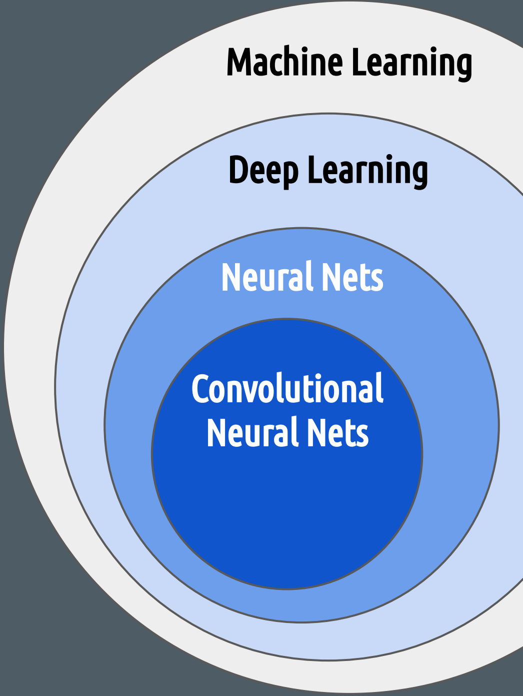


Image recognition



Decision Trees

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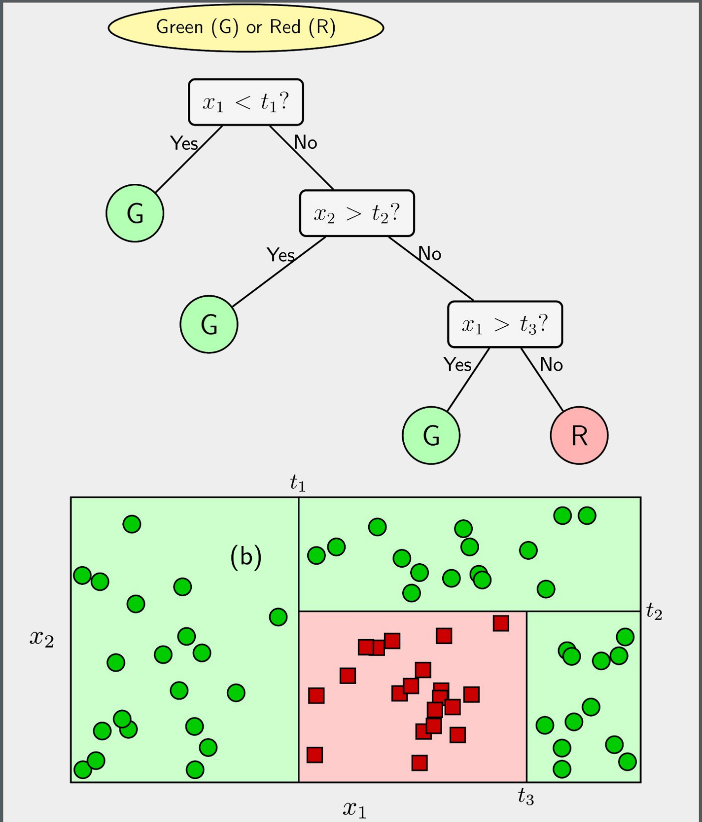
- Decision trees are the simplest form of machine learning
- The thresholds and position of each decision node are varied until error is minimised.

Problems:

- Decision thresholds are linear (eg 1D)
- Requires input of ‘features’ derived from data



Robovetter - Decision Tree

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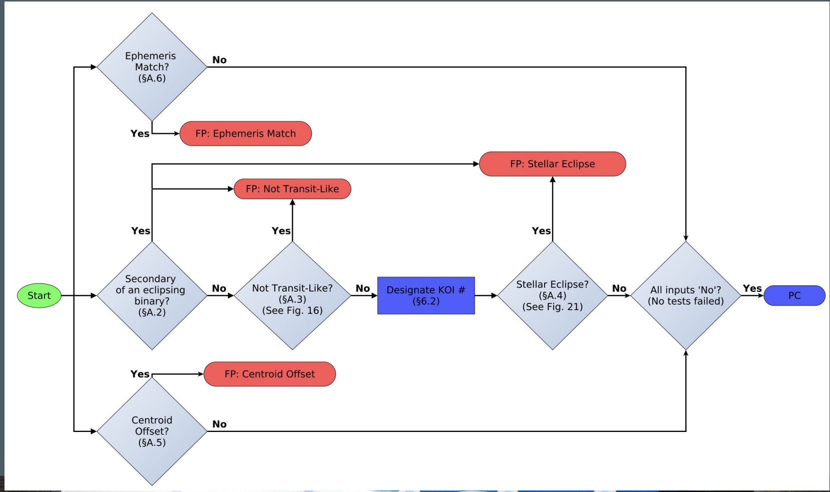
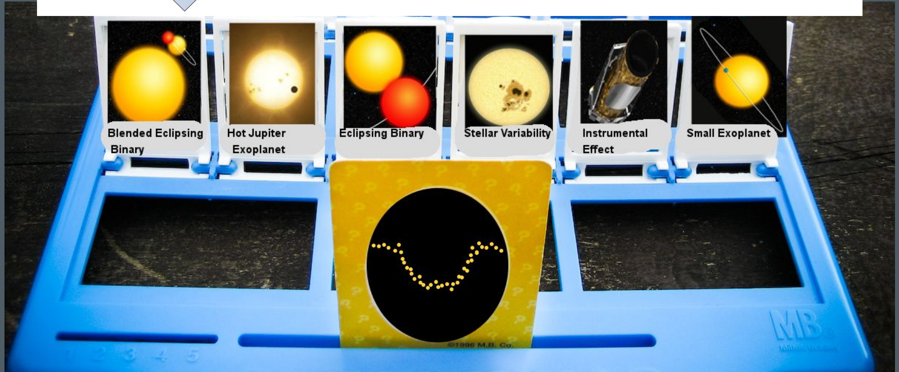
"Robovetter" - Thompson et al 2017.

Decision tree classifier used to produce Kepler's homogenous catalogue in DR25.

Used features processed from lightcurve.

Achieved a recall of around 80% on injected data.





Random Forests

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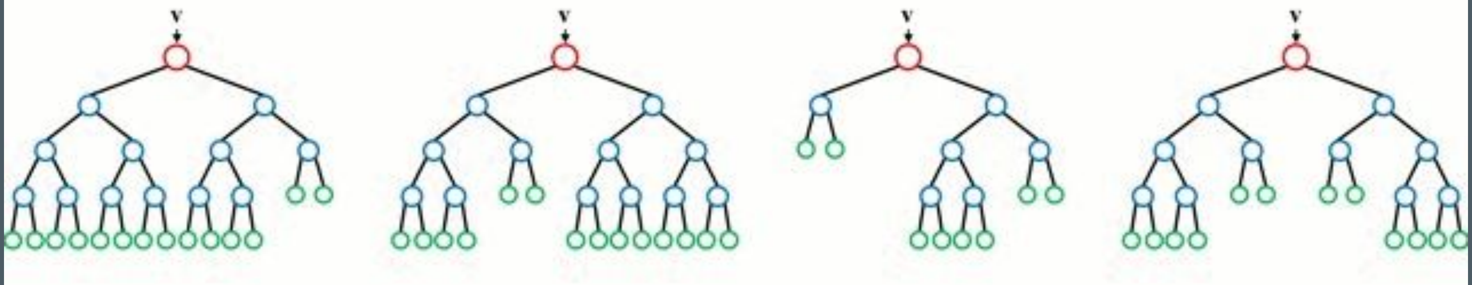

- Each tree sees random subset of whole dataset
- Each decision step uses random selection of available features.

Random Forests

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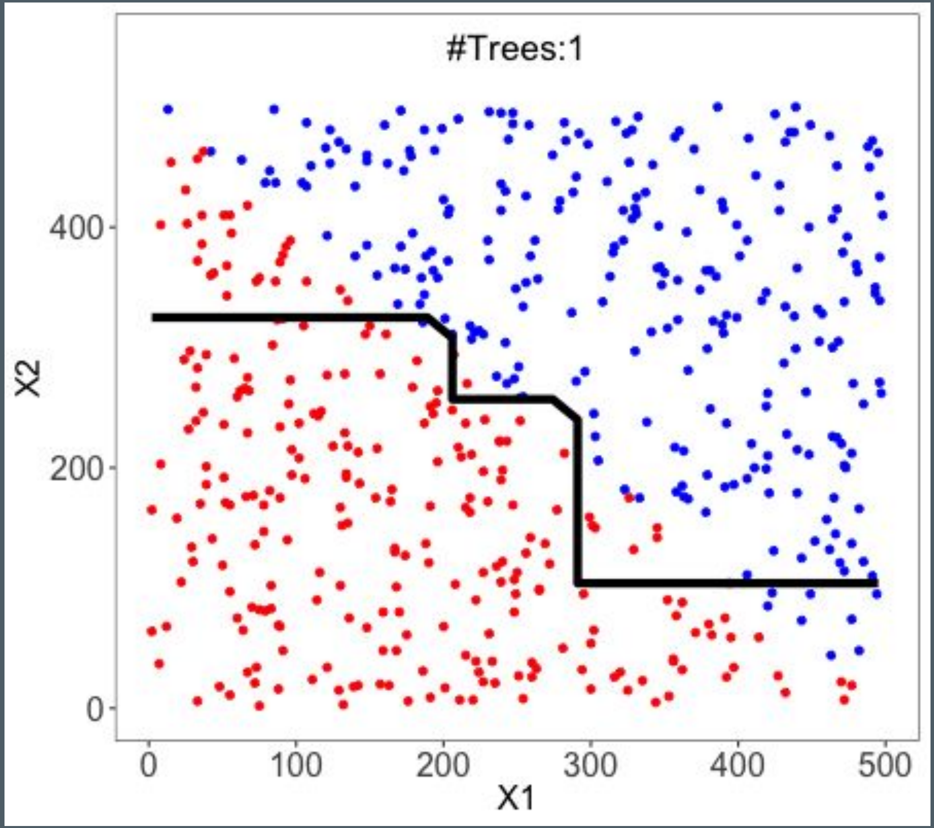
- While each tree splits the data "linearly", averaging of many trees approximates non-linear splits in data.



R.F.s in exoplanet atmospheres

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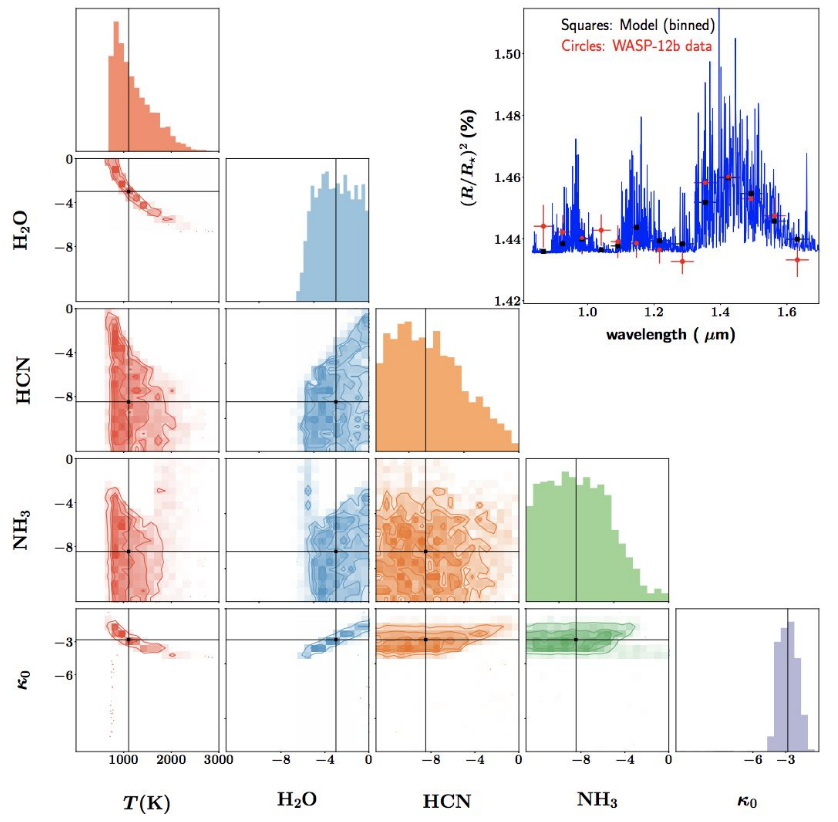
Marquez-Neila et al (2018)

Random Forest for atmospheric retrieval.

Inputs: HST transmission spectra of WASP-12b.

Outputs: 5-parameter model of exoplanet atmosphere.



Autovetter - Random Forests

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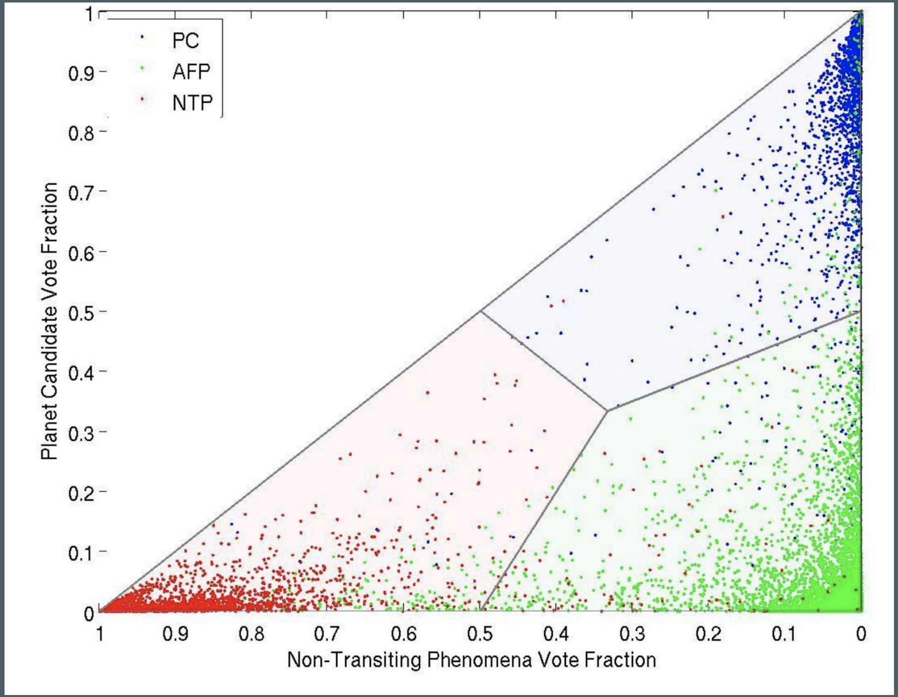
The Kepler team also produced a random forest - MacAuliff et al, (2015)

Used 230 features calculated from candidate lightcurve, model fits, etc.

3 output classes: planet, astrophysical dip (e.g. EBs) & non-transiting phenomena

94.15% accuracy & 97.2% average precision (on human-labelled data)



Exoplanet Classification with KNNs

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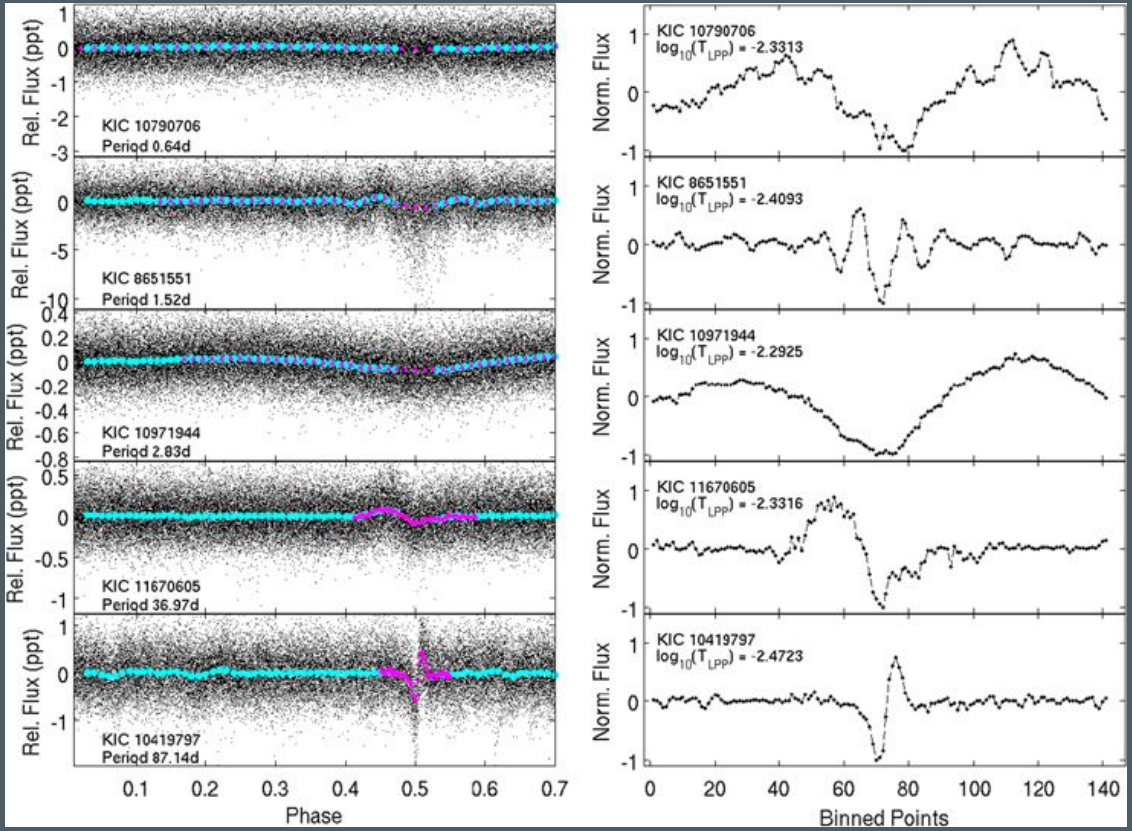
Thompson et al (2015).

Used a "K-Nearest Neighbours" (KNN) unsupervised approach.

Takes average of nearest labelled features.

Used as inputs binned & normalised phase-folded transits.



Neural Networks

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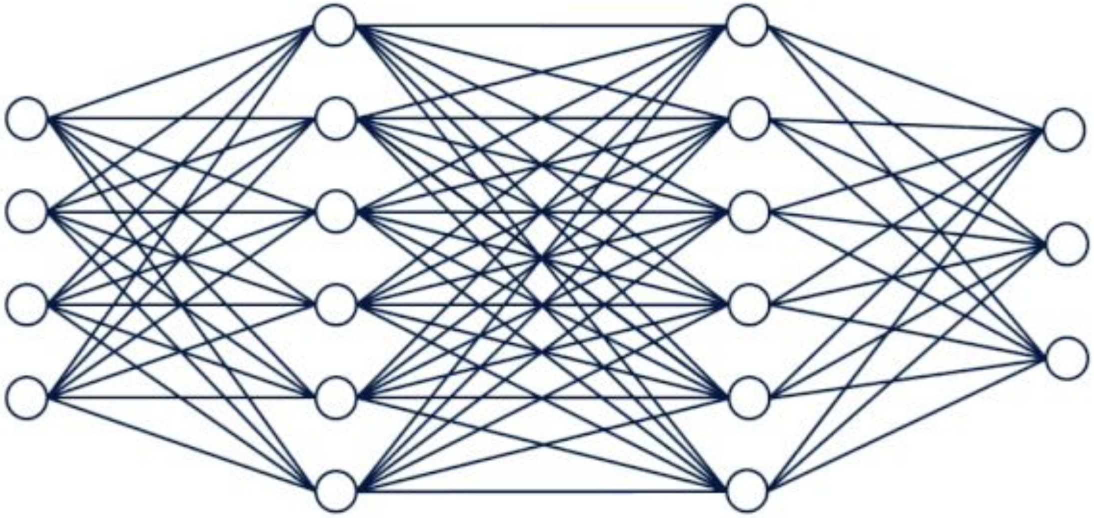
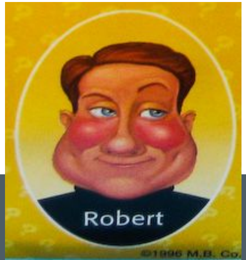


Hidden Layers



Neural Networks

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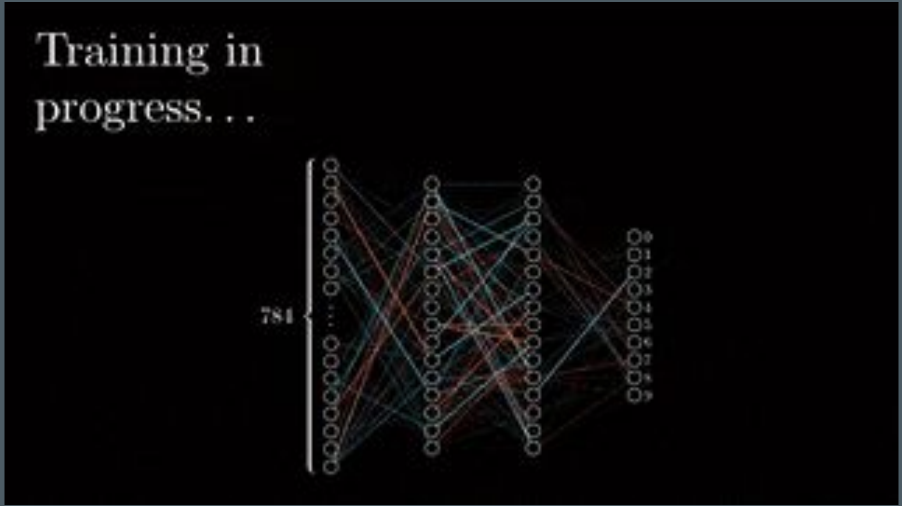
Training neural networks

- Quantify how poorly prediction was compared to ground truth
- Performance is then “back-propagated” through network to weights between neurons.
- These are adjusted such that the updated weight should decrease overall loss function - “gradient descent”



Neural Networks

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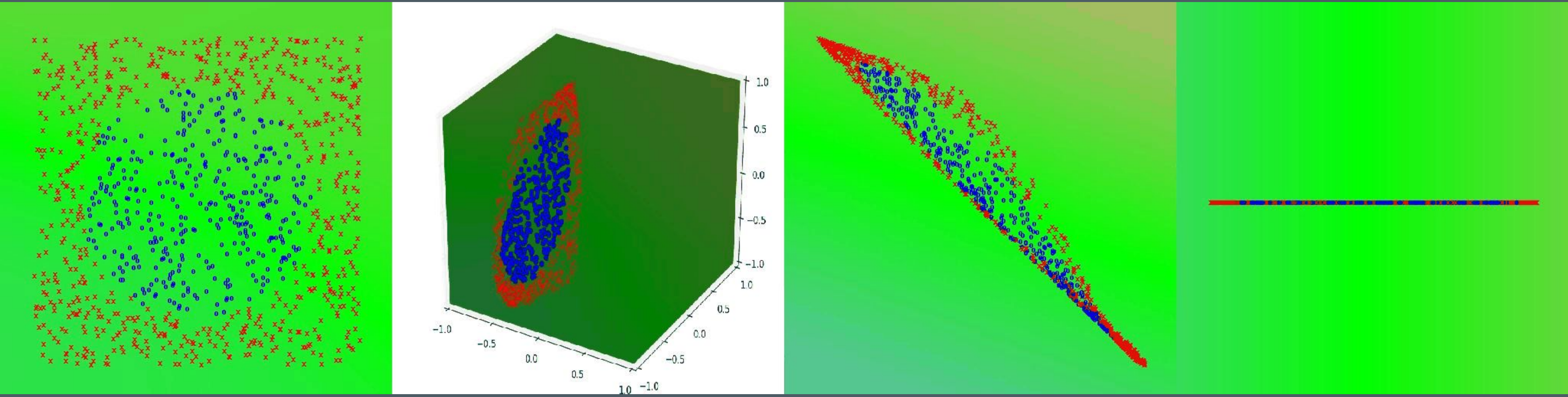
- Neural Networks are not inherently “linear” - can better map irregular parameter spaces
- Hidden layers allow “abstraction” - acts like a new dimension in which to “fold” the (lower dimensionality) data.



Unsupervised Learning (SOMs)

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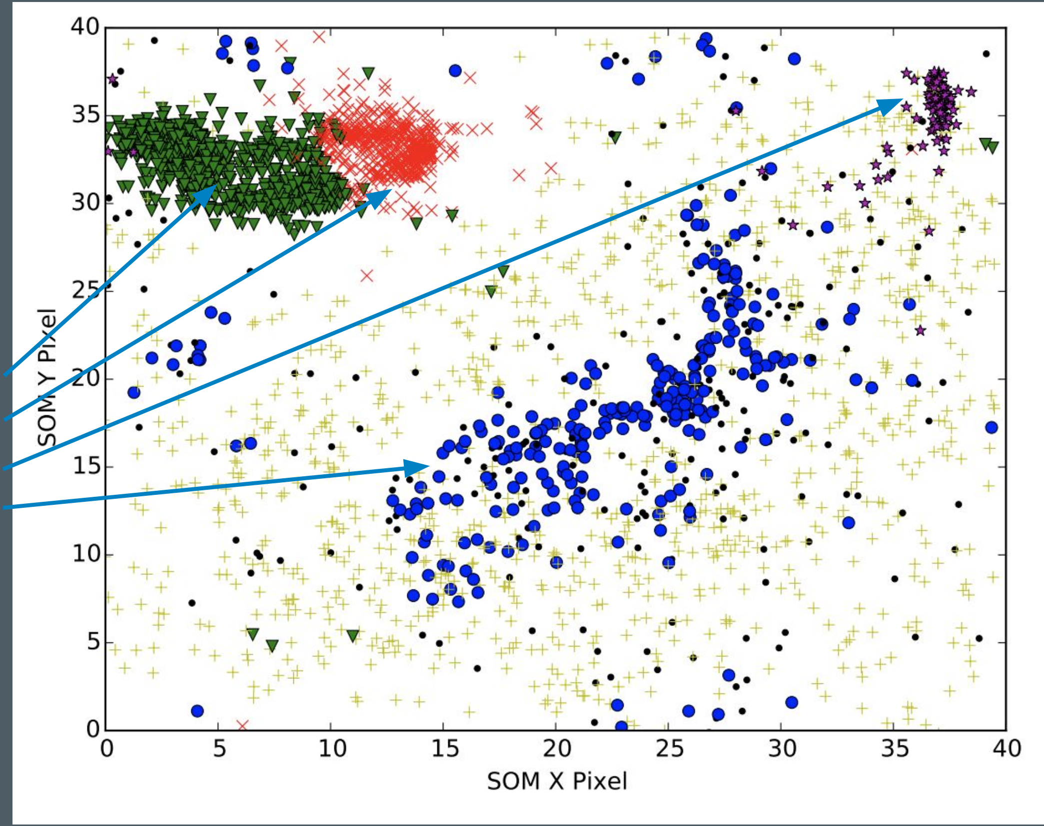
Armstrong et al, 2016

Self-Organising Map (SOM) - a type of neural network which reduces dimensionality without any supervision.

Creates isolated regions of self-similar input data

Performed on 4 K2 campaigns.

Pixel position used an input into Random Forest.



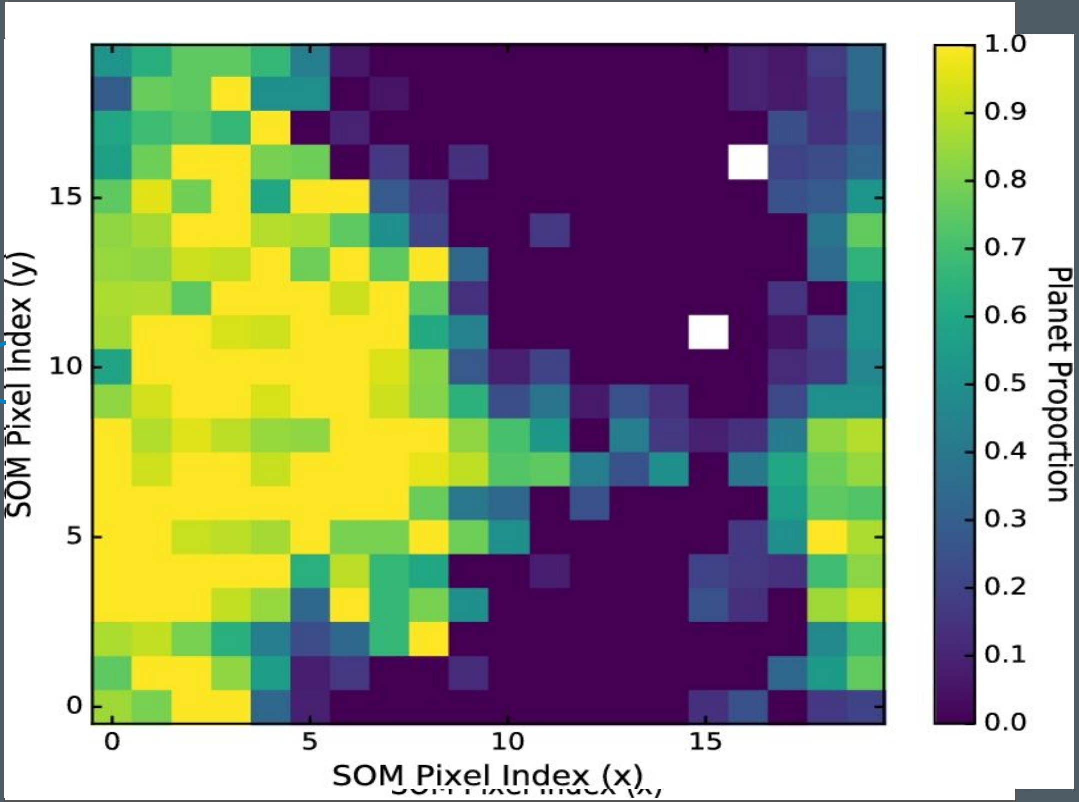
Self Organising Maps for Exoplanets

Armstrong et al (2017)

SOM and random forest applied to Planet candidates in K2 & Kepler

~79% accuracy on Kepler planets

EBs
Planets



Convolutional Neural Networks

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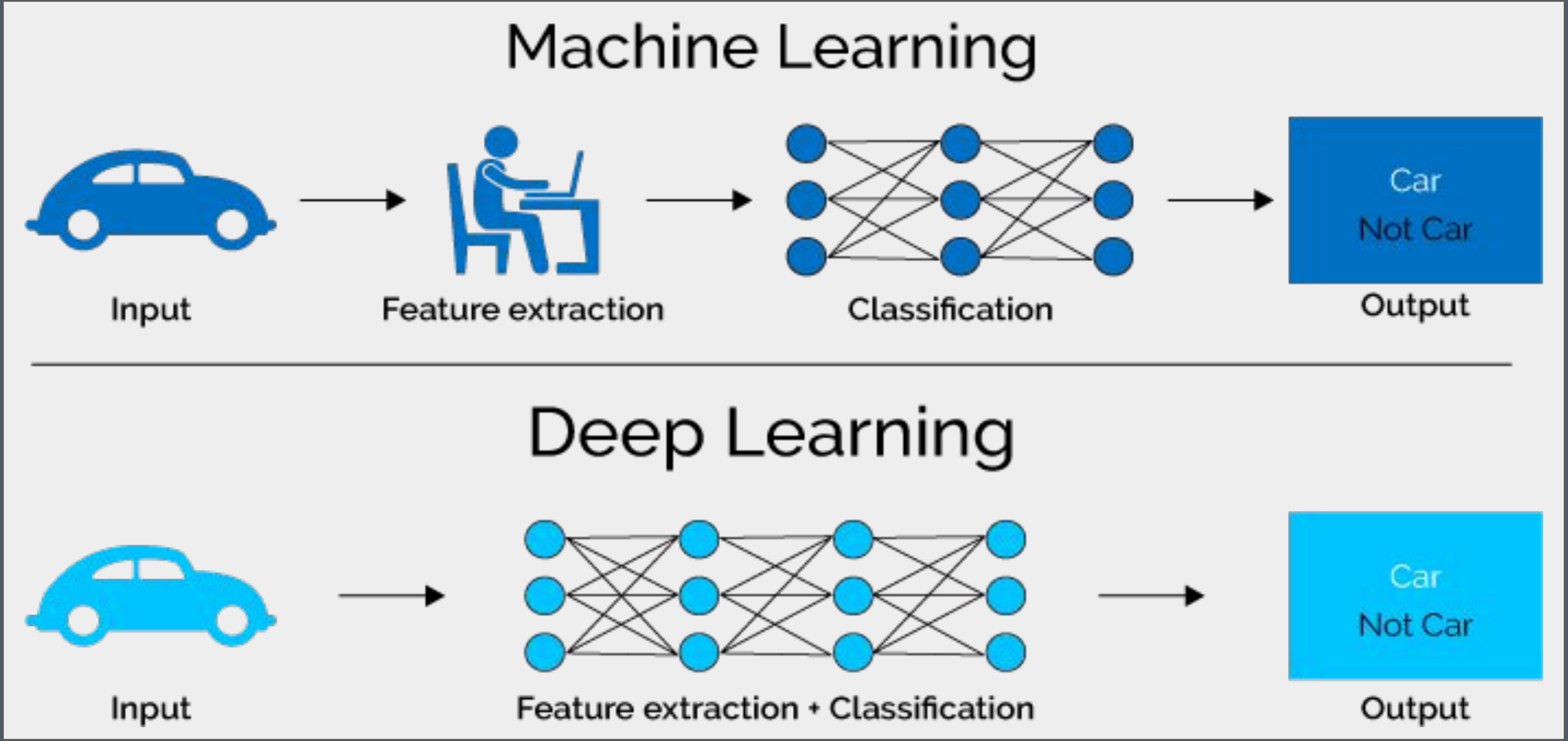

Convolutional Neural Networks

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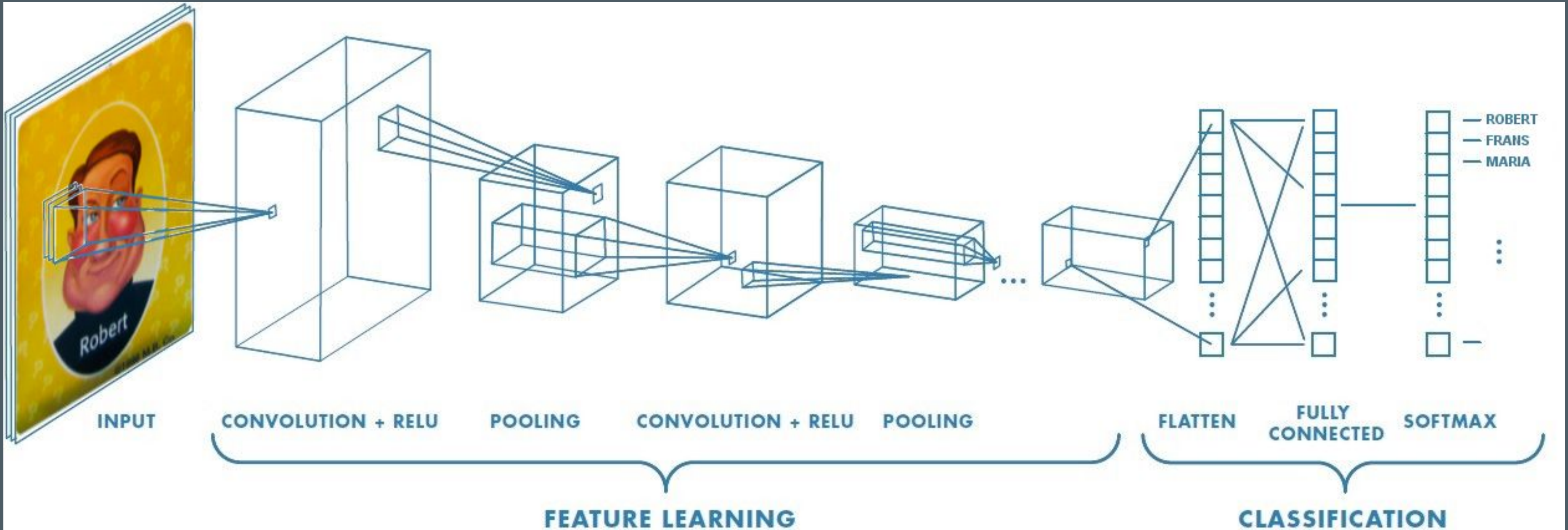

- Raw image "convolved" with range of filters (which themselves are trained with back propagation)
- Enables Feature extraction from the raw data (although raw data may need preprocessing)

CNNs for Atmospheric Retrieval

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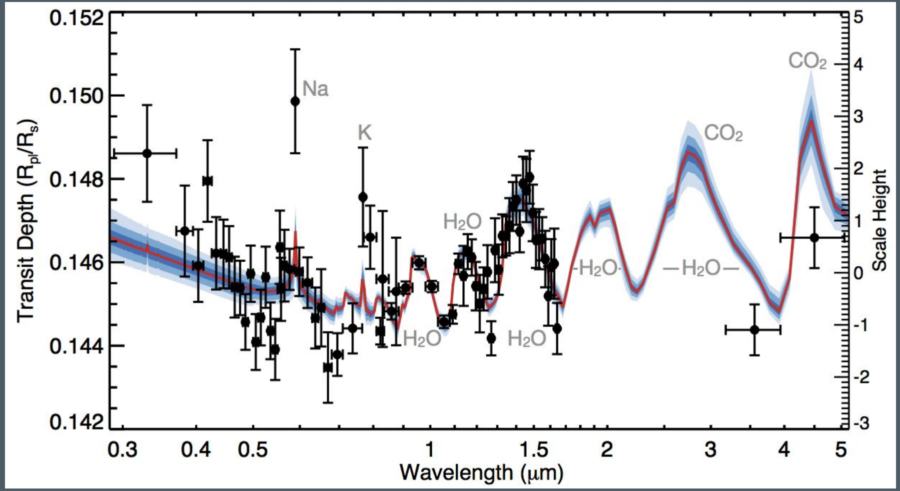
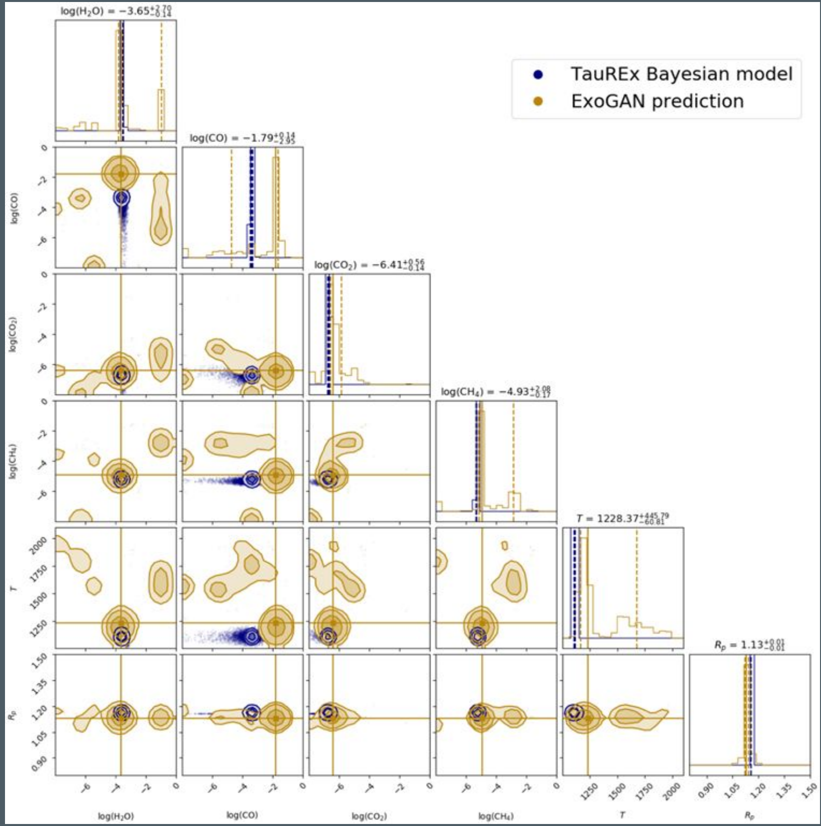
Waldmann (2015) & Zingales (2018) - RoBErt using Neural networks

Cobb, Angerhausen, et al (subm.)





Ground-based transits with RF & CNNs

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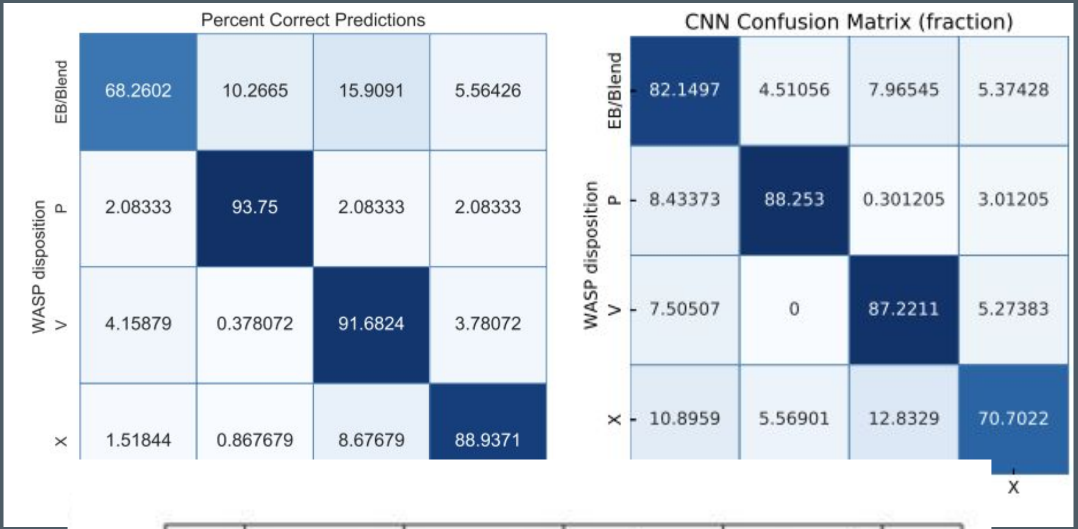
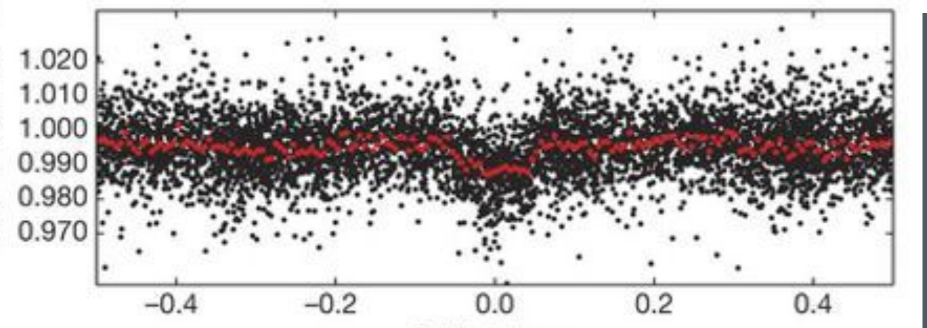
Schanche et al. (2018)

Classified WASP planet candidates with both Random Forest and Convolutional Neural Network.

CNN gives better average precision, but random forest performs best on planets:



MEarth used Neural Networks to determine which “triggers” the telescopes should follow, leading to LHS 1132 b Dittman et al. (2017)



CNNs for Exoplanet Detection

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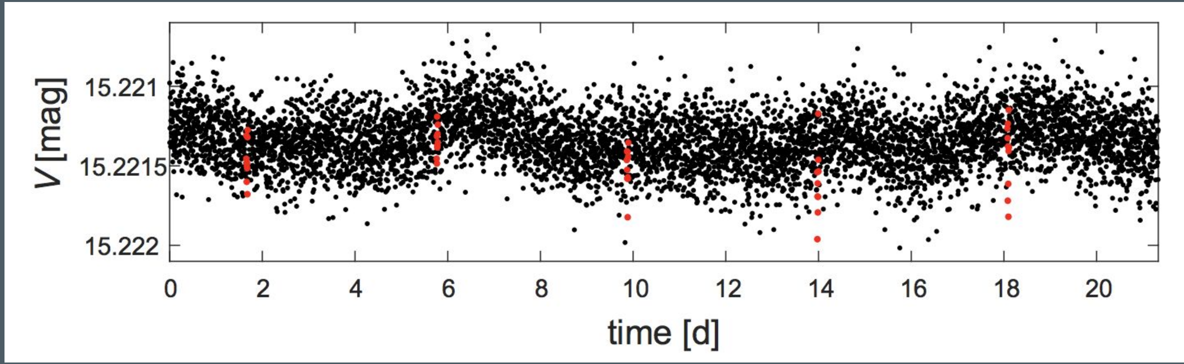
Two parallel papers using neural networks to detect exoplanets:

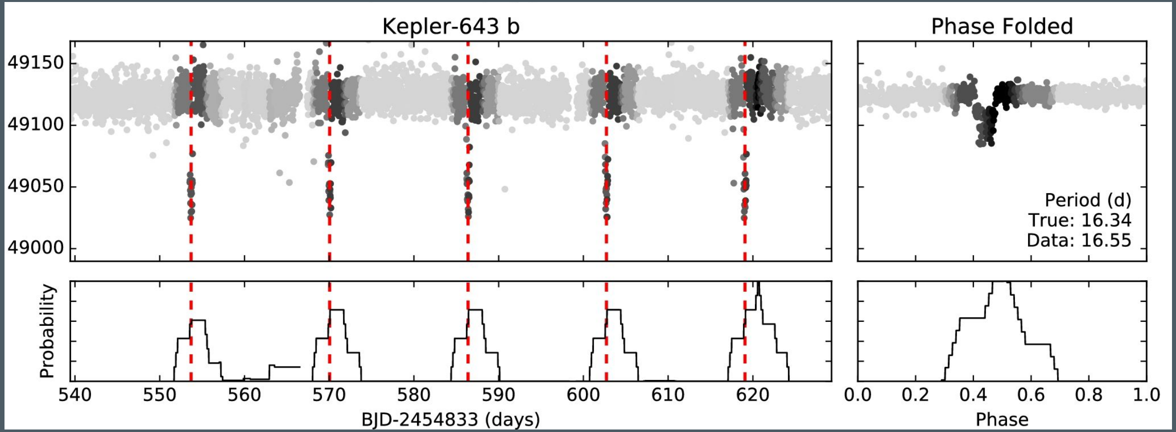
Zucker et al, (2017)

Pearson et al, (2017)

Difficult as neural networks cannot natively learn “periodicity”.

Neither deal with classifying real planets vs false positives

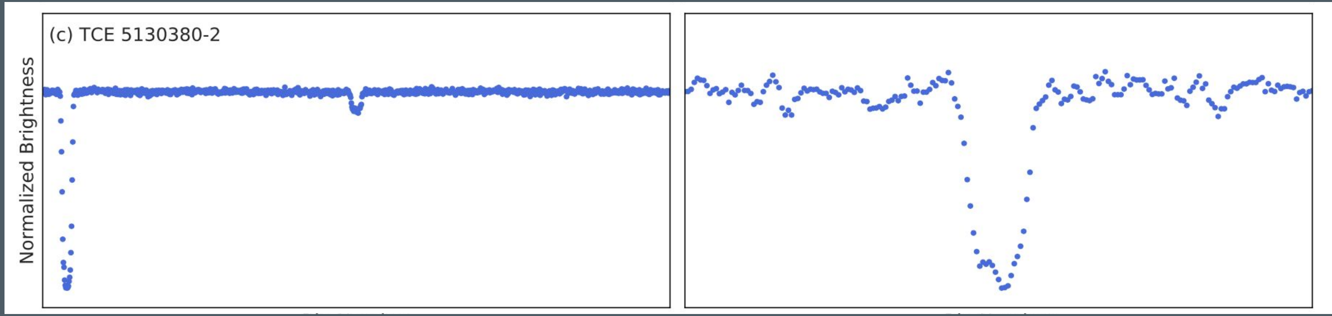


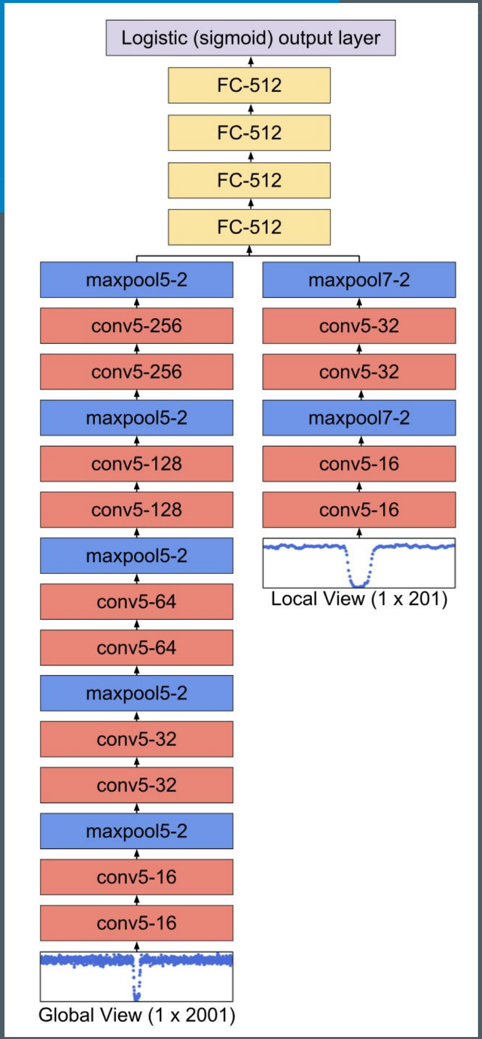


Shallue et al 2018

Astronet - Shallue & Vanderburg (2018)

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





New planets from CNNs

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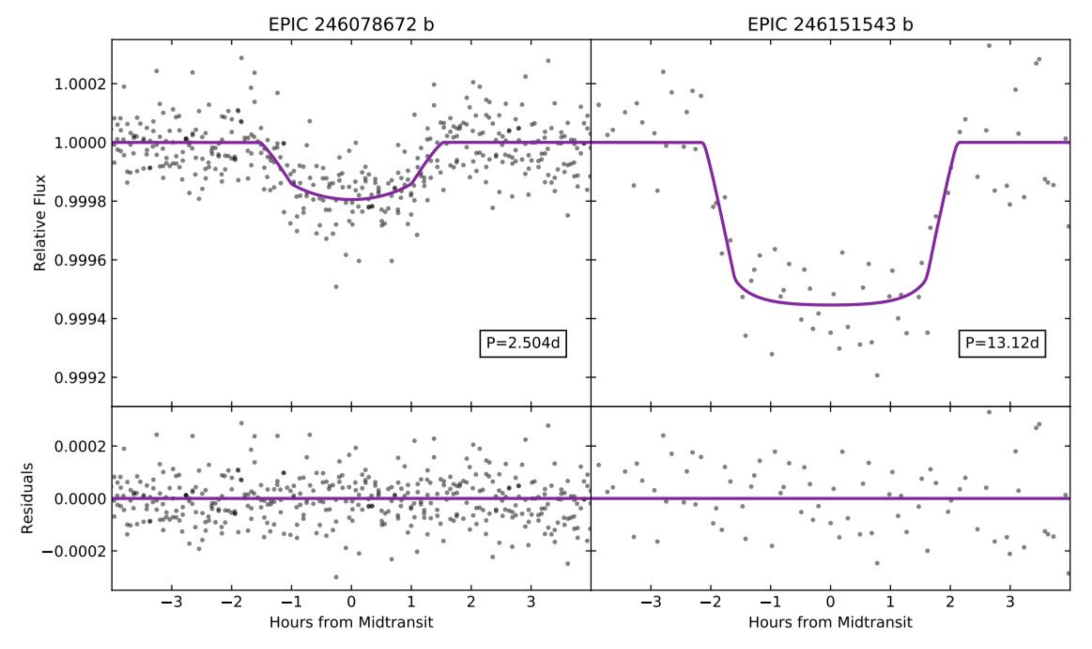
Dattilo et al (Yesterday)

Using the methods of Shallue & Vanderburg, they detected new candidates in K2, including two statistically validated planets.

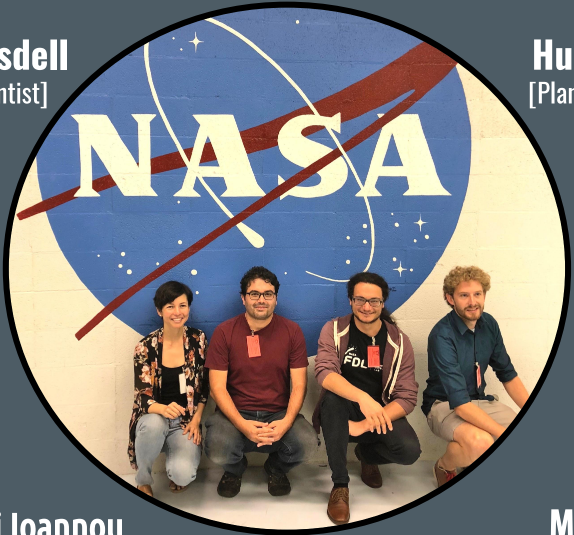


Our FDL project:
Can we do better?

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. Raissi (INRIA), Yarin Gal (Oxford)
- *Compute Power* → Massimo Mascaro (Google Cloud)

Paper 1: Classifying Kepler Candidates

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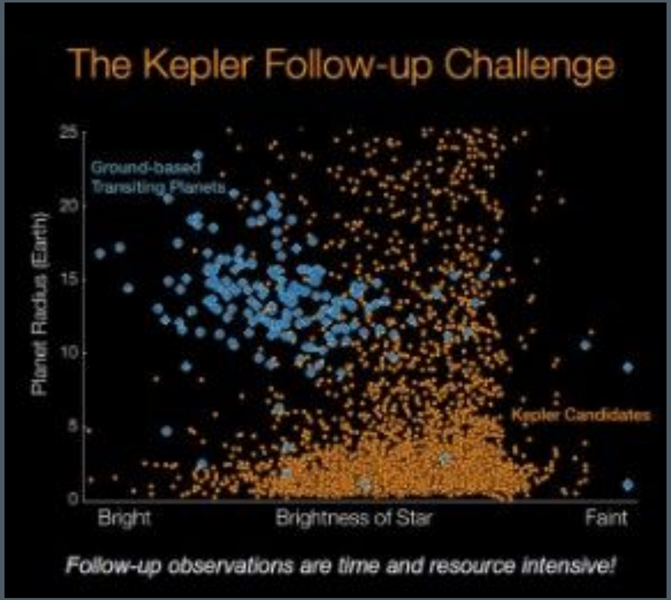
- 16,000 Threshold Crossing Events (TCEs) from Kepler DR24
- Labelled by human vetters
- ~25% planets & ~75% false positives
- Followed Shallue & Vanderburg to preprocess the data:
  - Detrending lightcurve
  - Phase-folding onto candidate period
  - Binning to “global” & “local” view

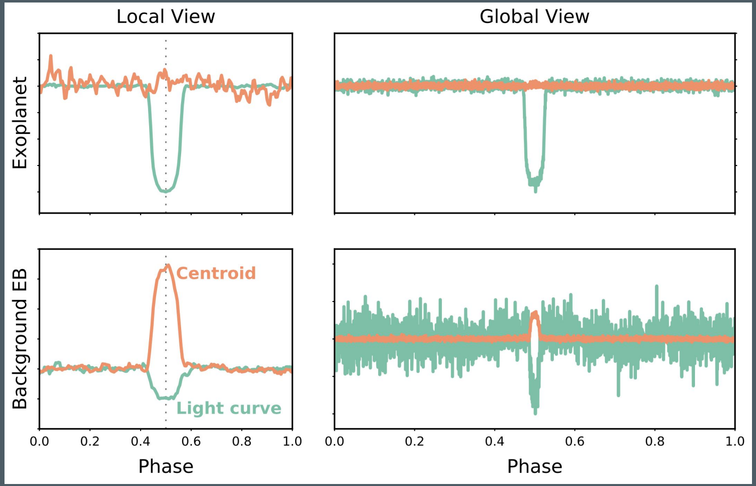


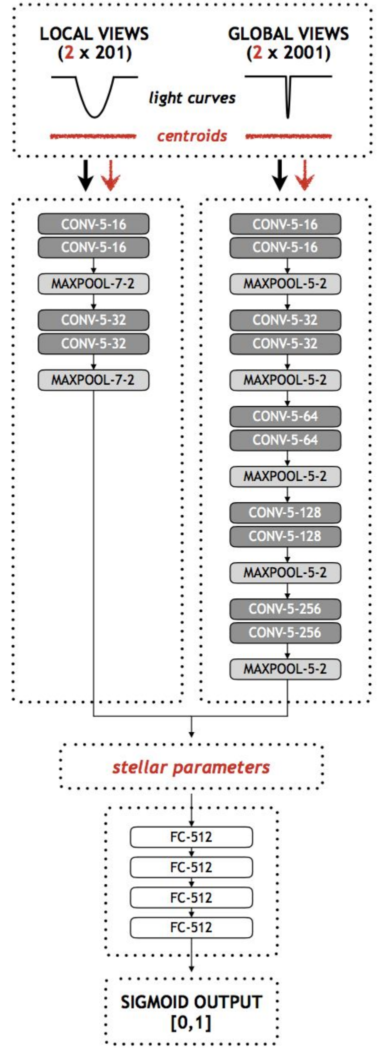
Ansdell, Ioannou, Osborn, Sasdelli, et al. (2018)

Classifying Kepler Candidates

Centroid Time-series

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



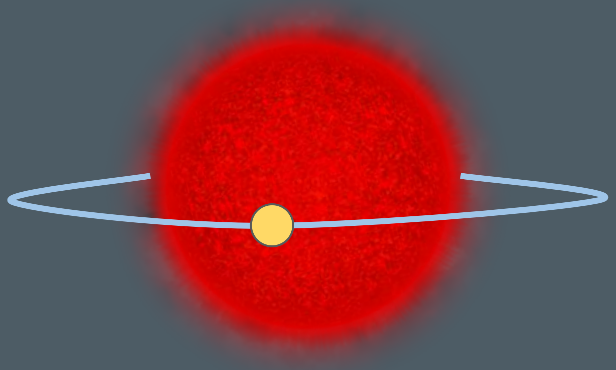


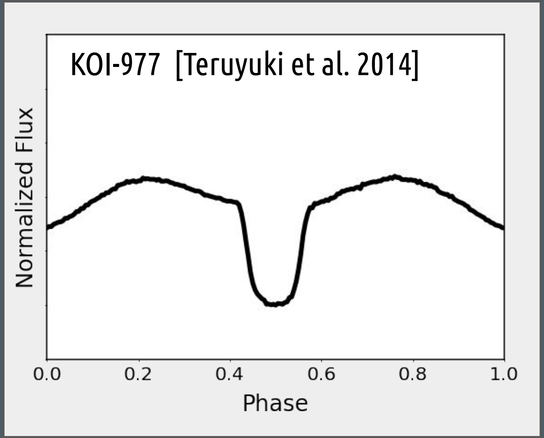
Ansdell, Ioannou, Osborn, Sasdelli, et al. (2018)

Classifying Kepler Candidates

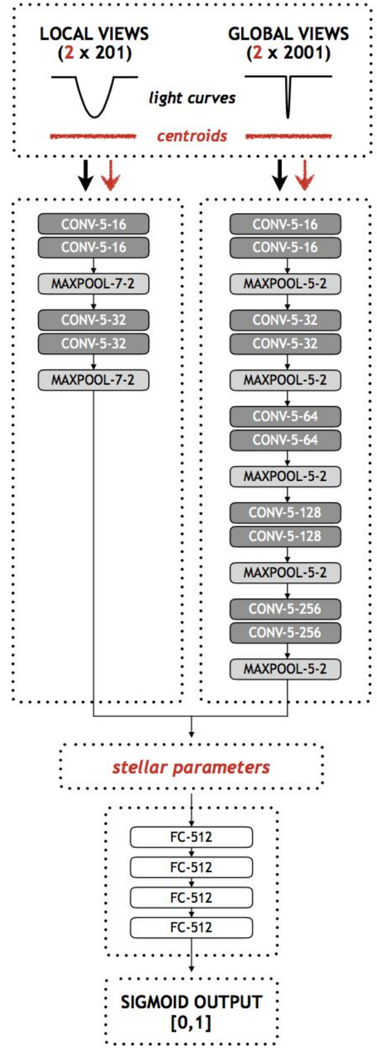
Stellar Properties

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





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



Performance on Kepler

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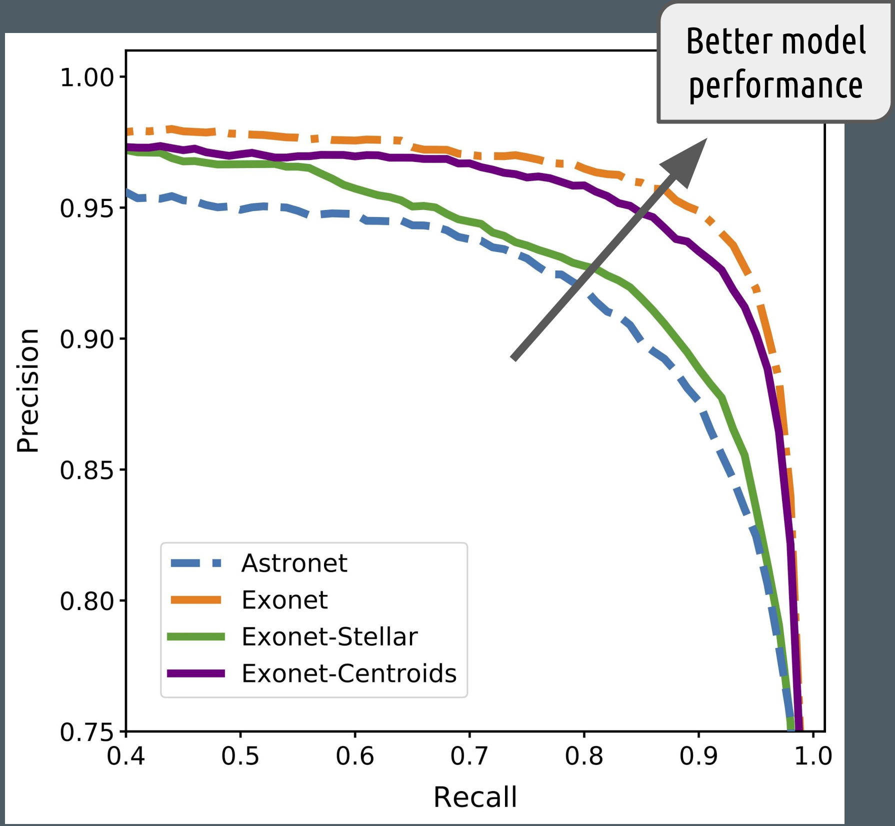
- Centroids & Stellar info both improve performance
- Cross validation & model ensembling also improved performance
- Best classification of any metric on Kepler

	Planet Accuracy	Avg. Precision
Autovetter	94.15%	97.19%
Astronet	95.8%	95.5%
Exonet	97.5%	98.0%



Performance on Kepler

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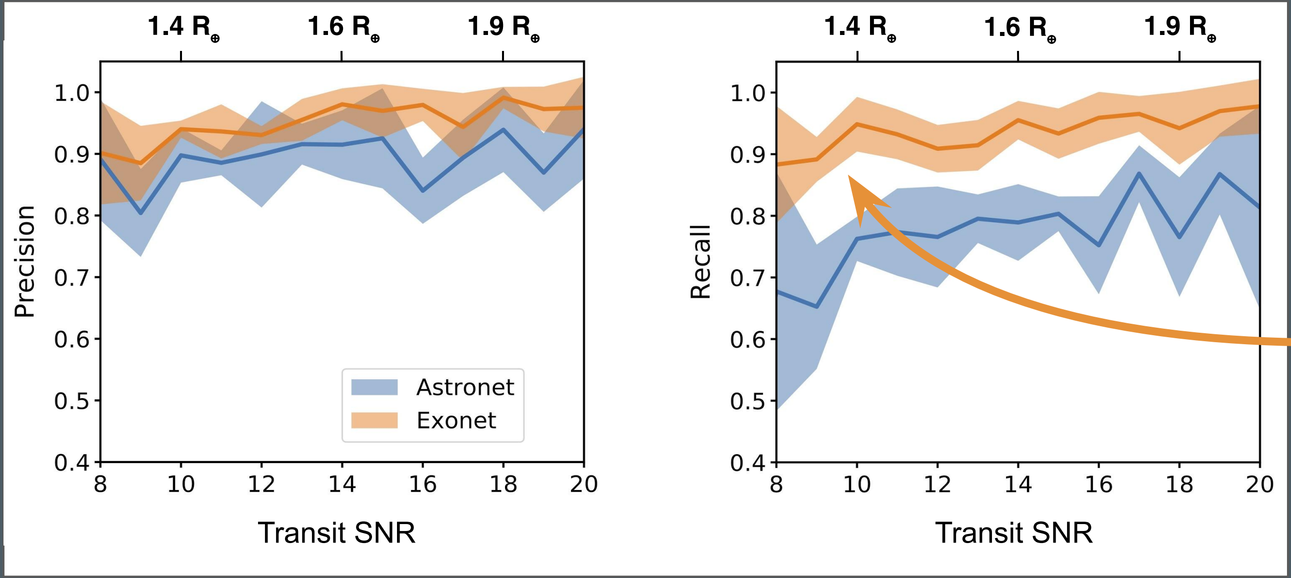
Improved Performance for Lowest SNR Transits

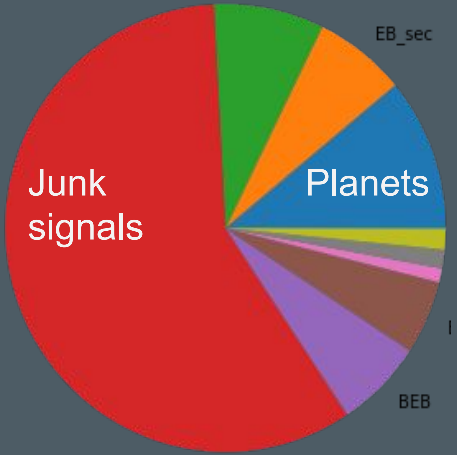


Future missions like TESS & PLATO will focus on small planets

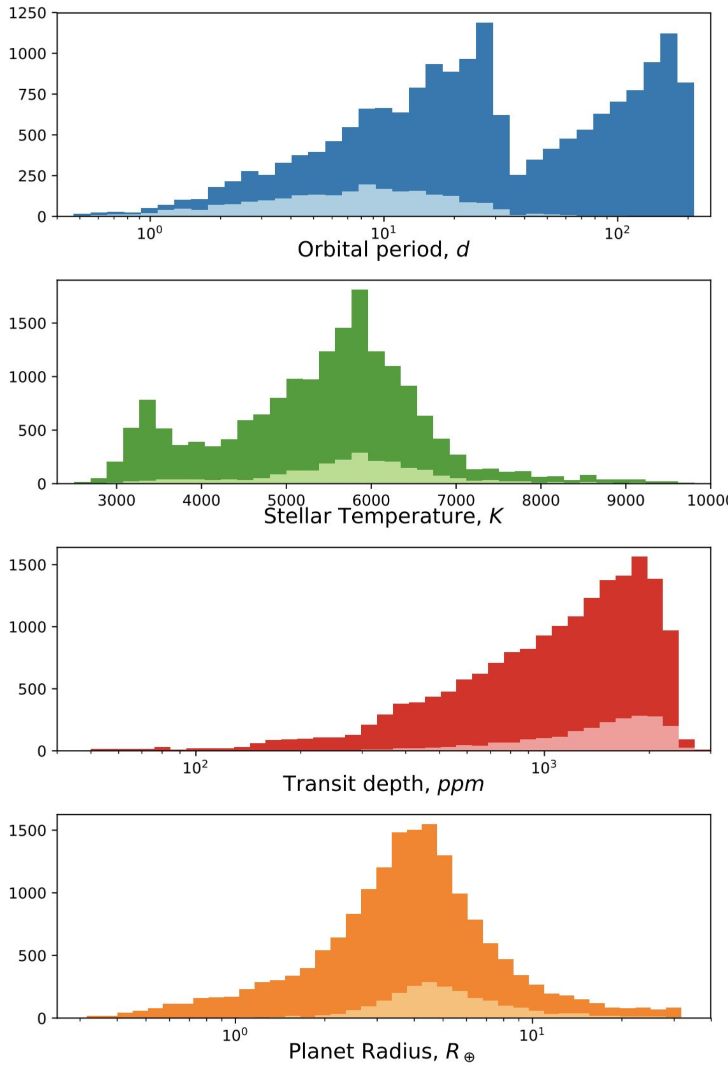
15-20% gains in recall for Earth-sized planets

Paper 2: Classifying TESS Data

- 4 Simulated sectors.
- Pixel-level injections of signals, processed with the full TESS pipeline
- ~16,000 candidates, with only ~14% planets



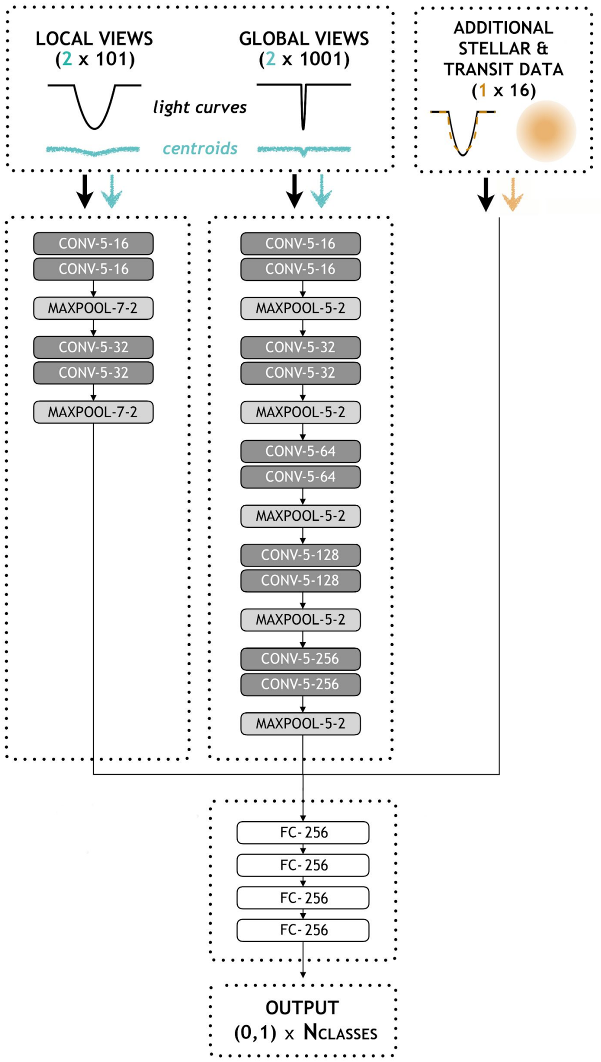
Osborn, Ansdell, Ioannou, Sasdelli, et al. (subm)



Classifying TESS Data

Modified the model of Ansdell et al (2019):

- Added additional transit-derived information
- Reduced bins from 2001 to 1001
- Used multi-class modelling



Osborn, Ansdell, Ioannou, Sasdelli, et al. (subm)

Data Augmentation

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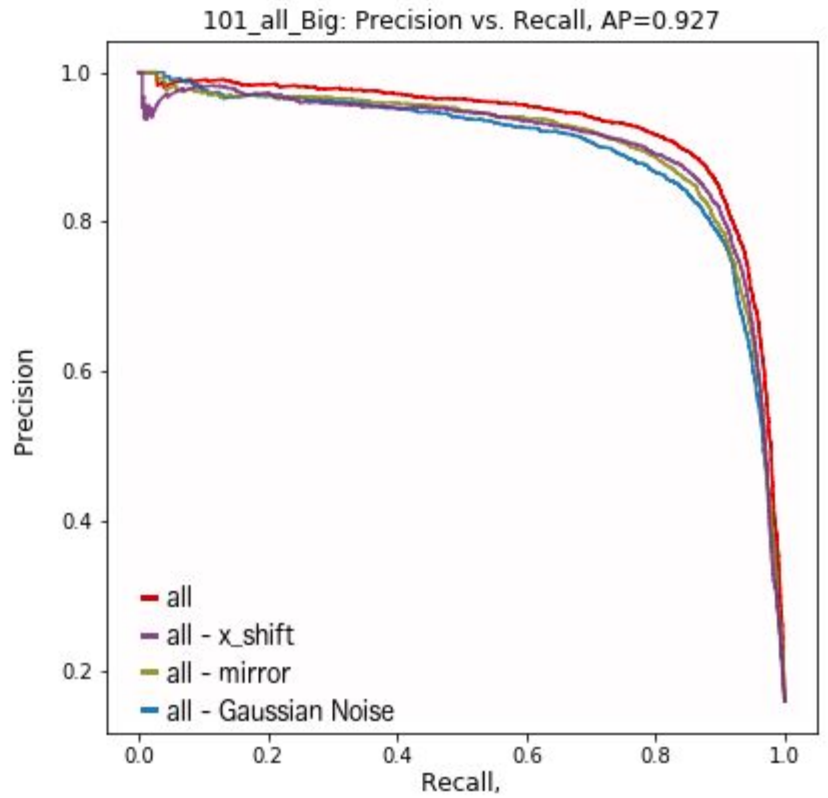
- Augmentation modifies input data to create "new" data for the neural net, preventing overfitting

	Avg. Precision
Exonet: no augmentation	85.2%
Exonet - Gaussian	89.6%
Exonet - xmirror	90.4%
Exonet - xshift	90.5%
Exonet - all	92.7%

Osborn, Ansdell, Ioannou, Sasdelli, et al. (subm)



Balanced Batch Sampling

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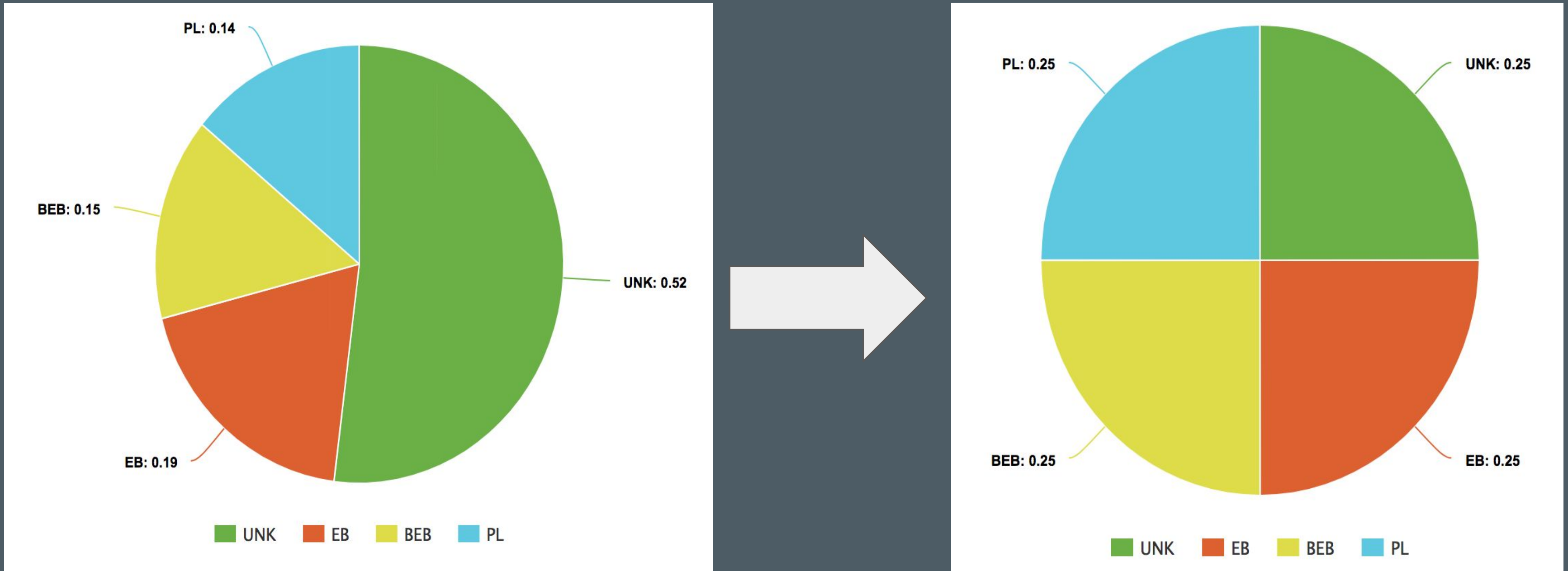
- Unbalanced data is difficult to learn as models tend to predict the majority class.
- Re-balancing means that each epoch sees same number of samples from each



Classifying TESS Simulations

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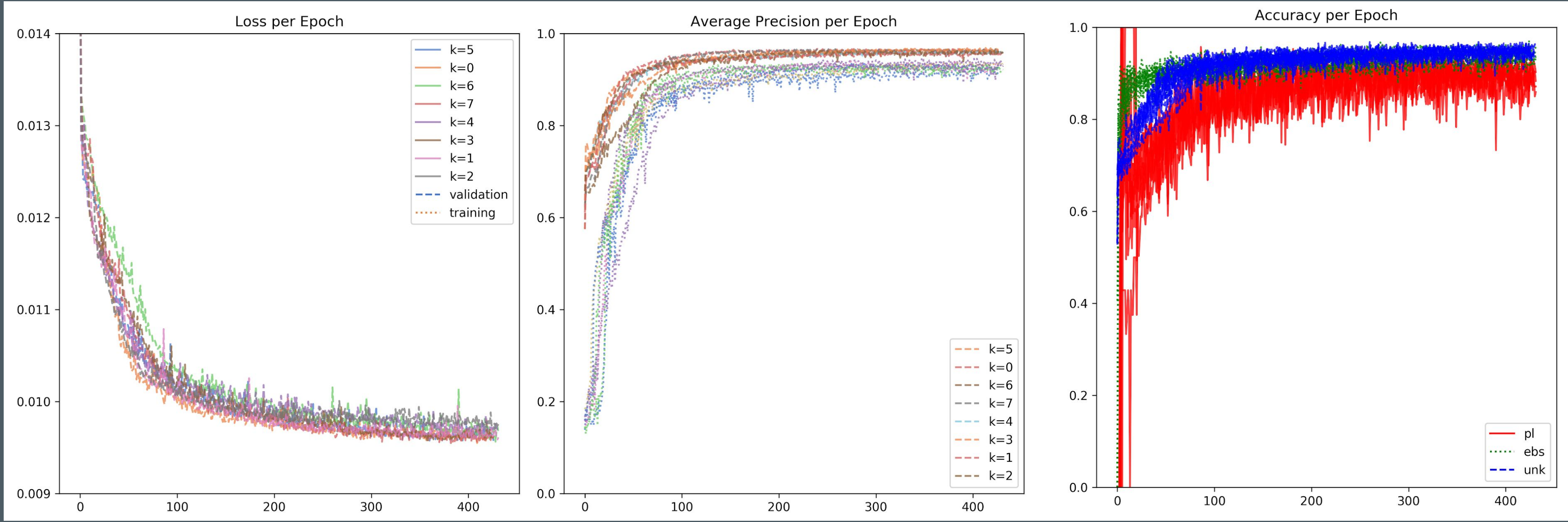

Osborn, Ansdell, Ioannou, Sasdelli, et al. (subm)

Performance on TESS Simulations

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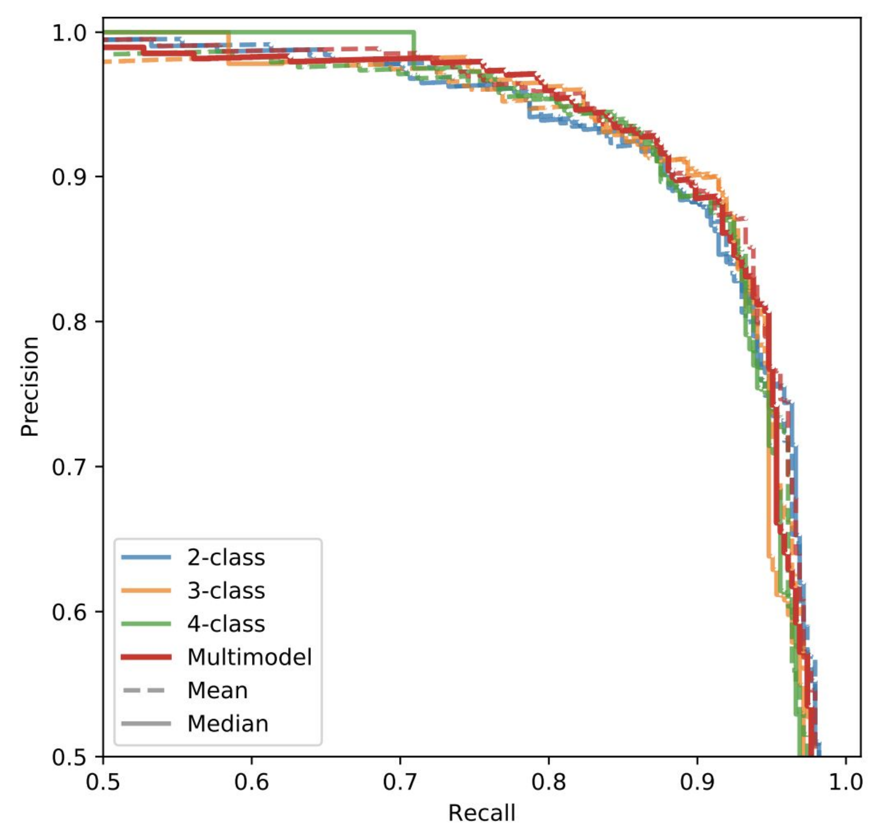
		Accuracy	Recall	Av. Precision
Binary	**Planet**	91.8	87.8	95.2
	Not Planet	97.6	98.5	99.4
3-class	**Planets**	90.4	90.1	95.6
	EBs	95.1	95.1	96.9
	Unknown	94.8	94.9	97.7
4-class	**Planets**	89.1	88.8	94.4
	EBs	87.4	91.7	94.7
	BEBs	88.5	81.7	91.7
	Unknown	94.6	95.5	97.8



Performance as a function of SNR

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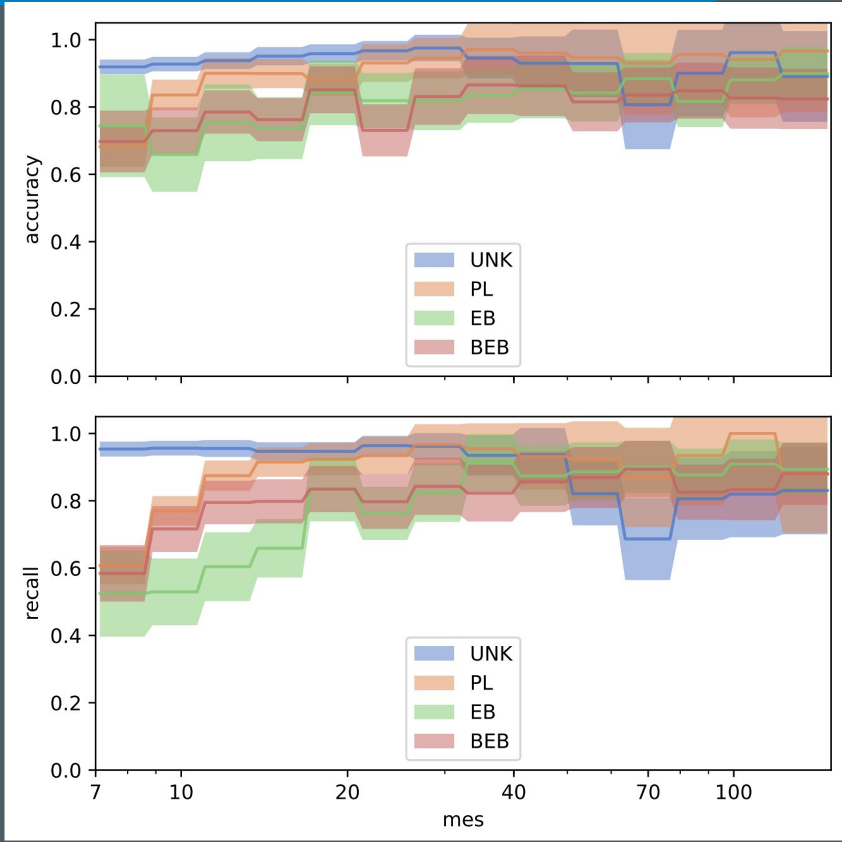
- Recall deteriorates at low SNR
- 70% accuracy in 7<SNR<8.5 range
- "Unknown" consistently accurate - model has learnt systematic features



3-class model

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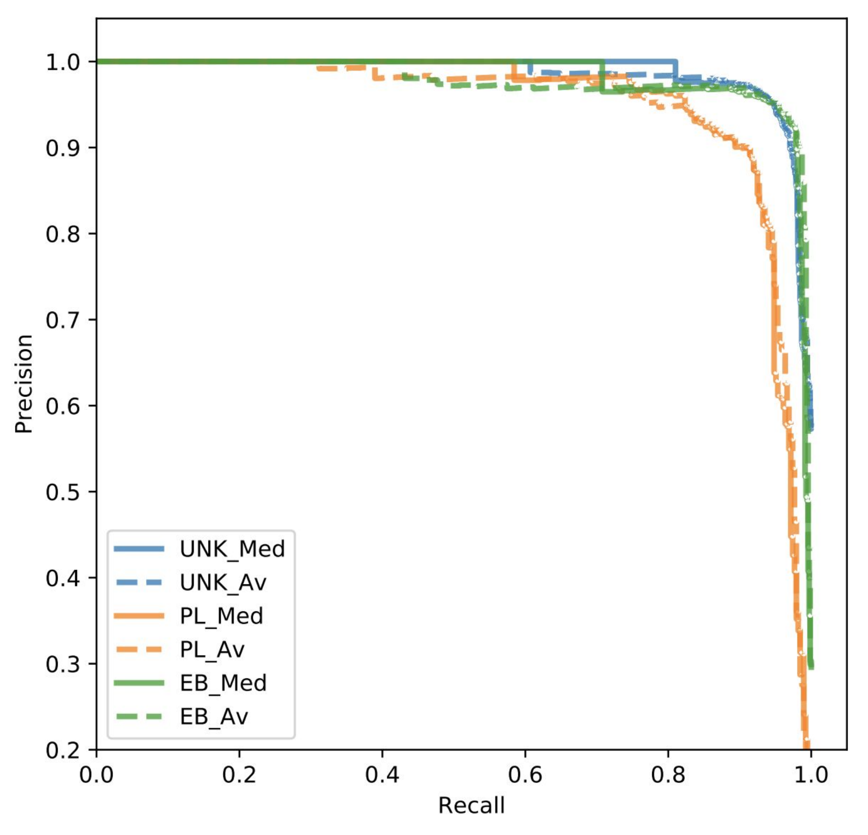

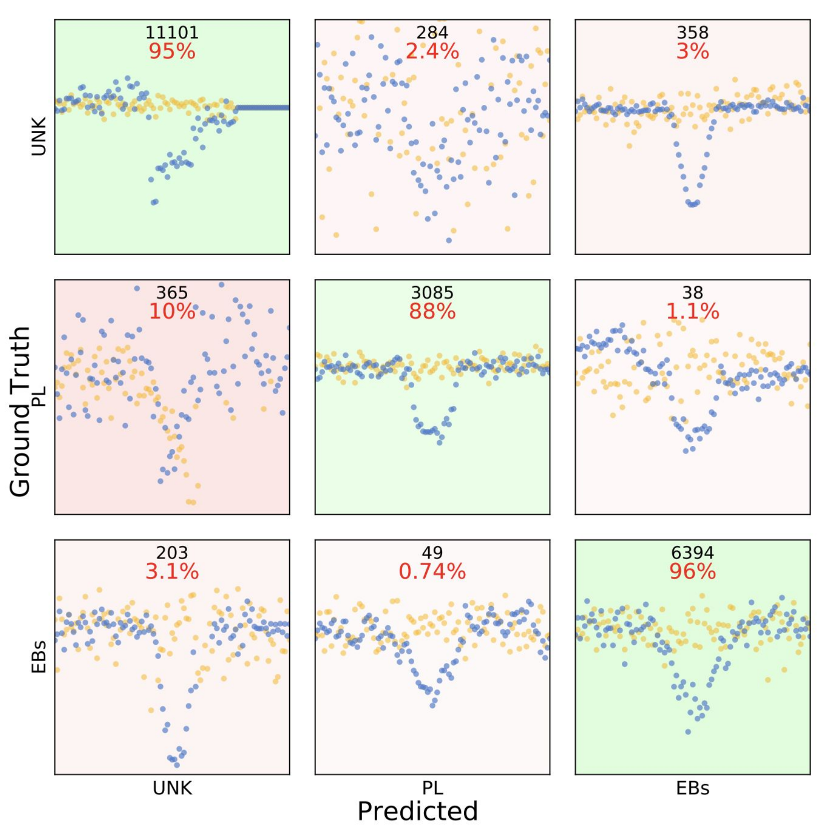

4-class model

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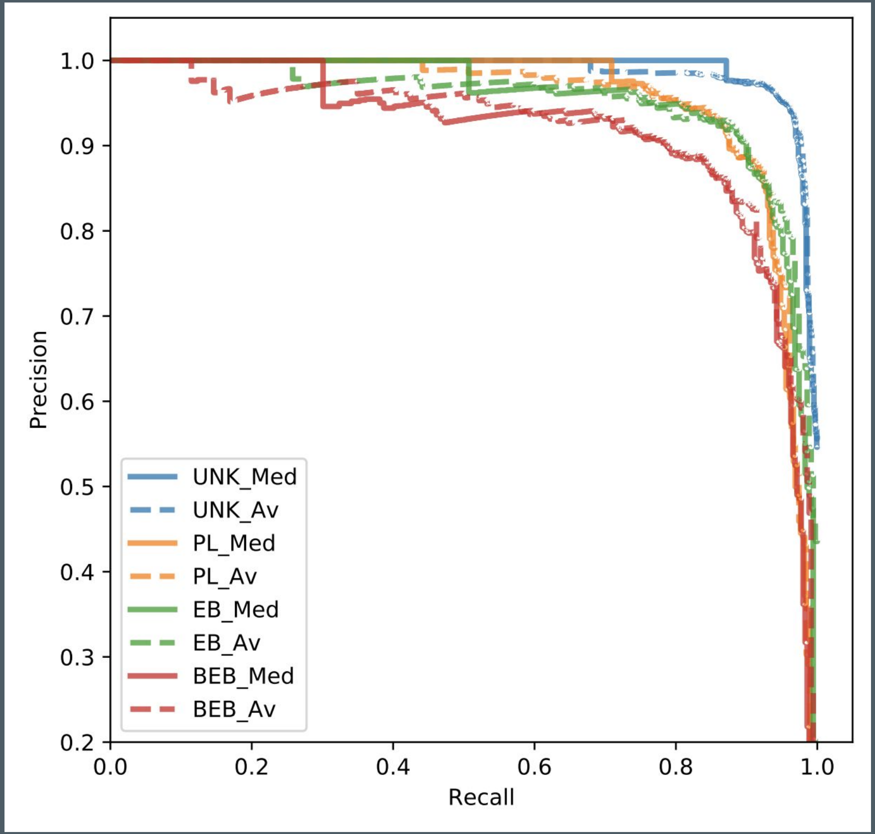

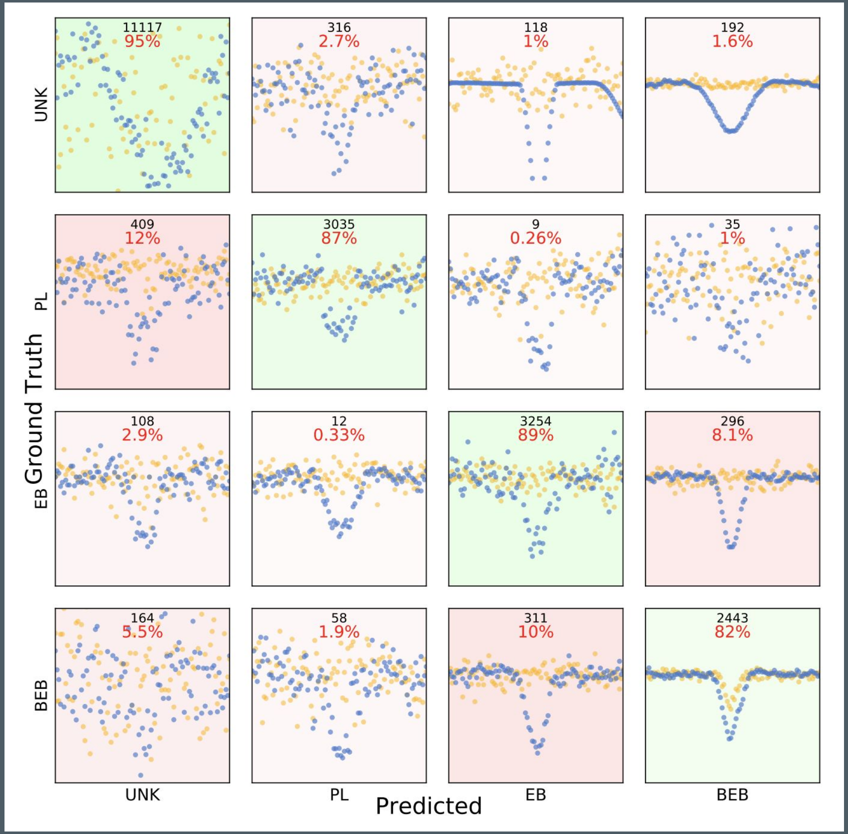

Comparison with Ansdell et al, 2019

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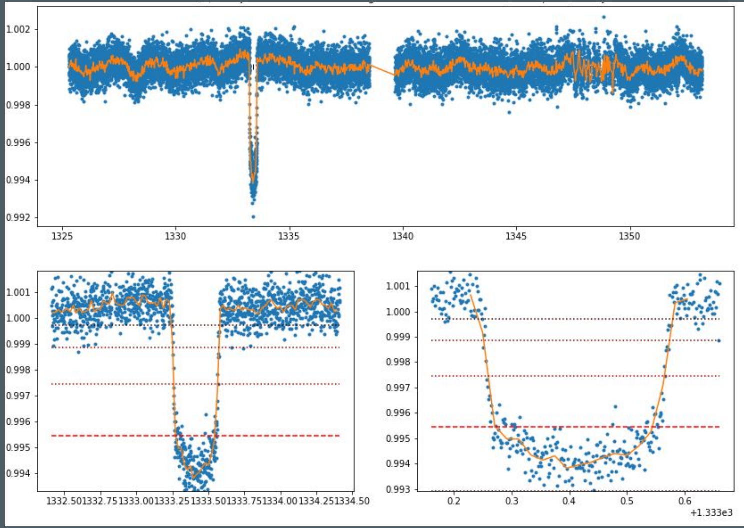
	Average Precision on planets
Kepler	98.5%
TESS	95.6%

← Why?

- Labels: Human vetting vs. Simulated ground truth
- Minimum transits: Kepler ≥ 3 - vs - TESS ≥ 2
- “Near misses” - 196 “false positives” are planets
  - 44% from monotransits
  - 25% from period confusion
- Including “near misses” - planet accuracy from 90.3% to 95.1%



A Monotransit flagged as periodic in real TESS data.

Application to real TESS data

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Far faster than other TESS vetting methods!

- ~60 minutes to pre-process lightcurves
- 5 minutes to predict with trained model on one GPU

But real data ≠ simulated data

- Different noise characteristics
- Do injections match reality?
- No “ground truth” to make comparisons

TESS has 2 candidate pipelines producing candidates. Overlap is not perfect.

Application to real TESS data

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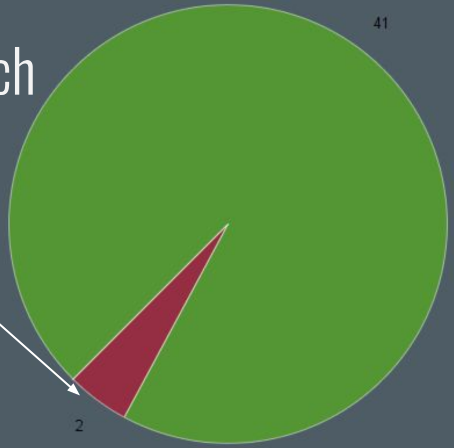
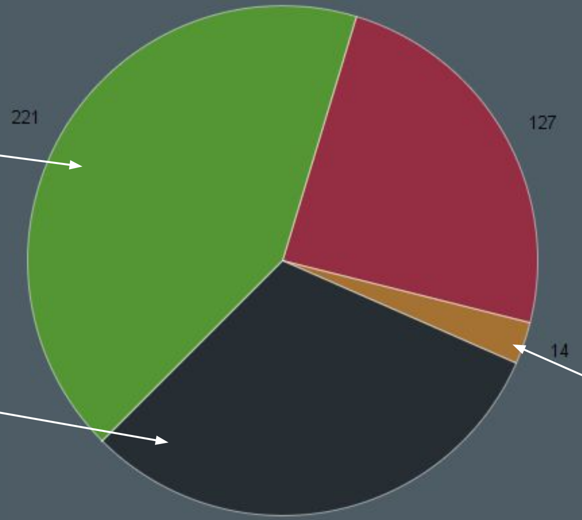
Planets Known Before Launch



HATS-34b: shows secondary
WASP-18b: b=0.94 (grazing)

All KOIs in Sectors 1-5



Recall of 61% on KOIs

KOIs from QSOP pipeline not in our candidate list

14 we suggest are EBs

New predicted planets

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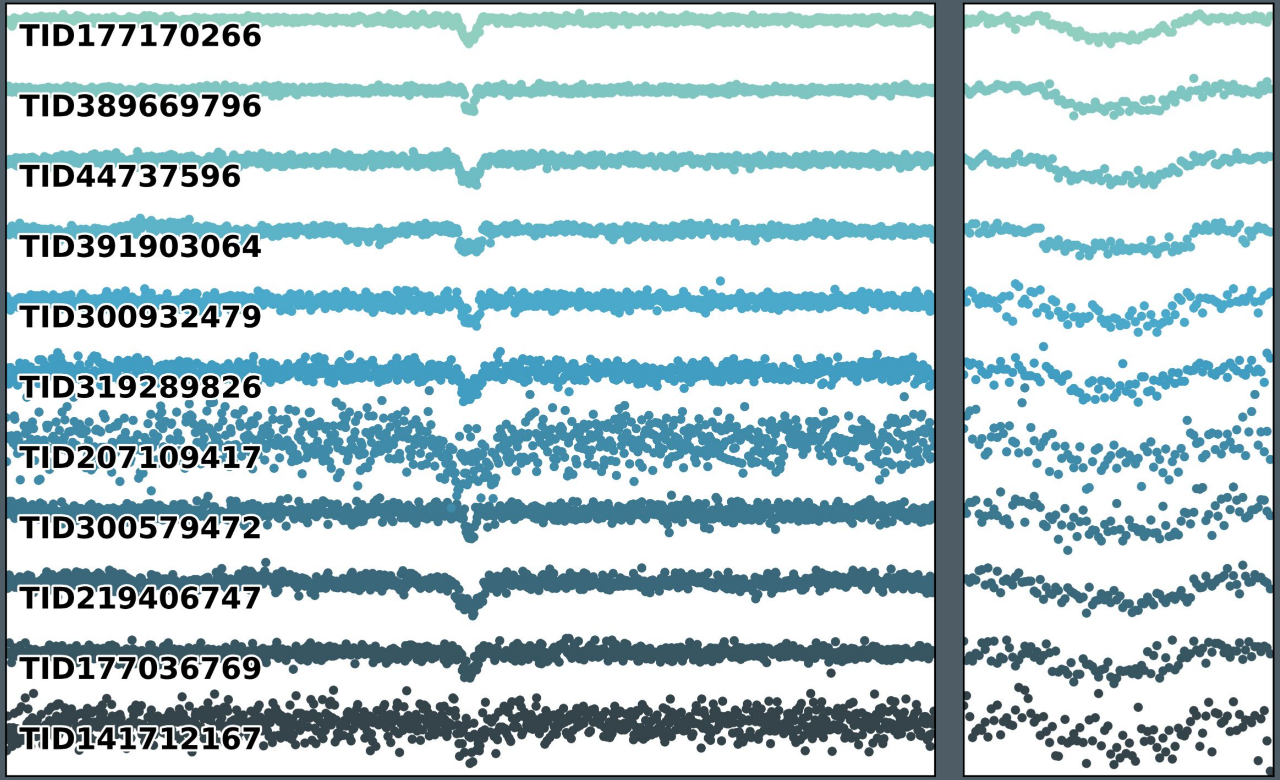
>100 new candidates predicted

Problems:

- Many giant binaries in predicted sample
- Some of these targets share the same period and epoch - reflections from a bright binary



Future steps

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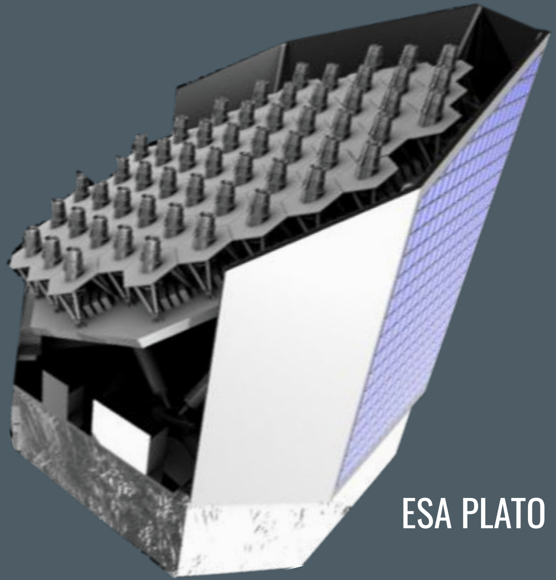
- Train with real TESS lightcurves
  - Problematic: how to inject signals and avoid real transit signals?
  - How to replicate instrumental effects many times?
- Add Bayesian Uncertainty to network
- Follow-up (and hopefully confirm!) predicted candidates
- Formulate how PLATO can use CNNs to classify & rank planet candidates



ESA PLATO

Conclusion

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- Machine Learning enables faster and often more accurate classification of astronomical data
- Our application to Kepler candidates is the best-performing model yet tested, with an accuracy on planets of 97.5%
- Our model on TESS simulated data shows CNNs are a promising method of rapidly classifying TESS planet candidates without human vetting, achieving between 90 and 95% accuracy.
- Application to real TESS data shows work is still needed, with a recall on KOIs of only 60%.
- Identified a handful of promising new candidates missed by manual vetters.

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Thanks!
Any Questions

Hugh Osborn

Podcast with
Andrew Rushby &
Hannah Wakeford

exo cast

@exohugh