Deep Learning for Exoplanet Transit Classification

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NASA FDL

FRONTIER DEVELOPMENT LAB

NASA Frontier Development Lab (FDL)

Space Scientists

Machine Learning Researchers

Silicon Valley Partners

FDL 2018

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

Innovative Solutions to Space Science Problems

Diverse & Interdisciplinary teams

Project:

Deep Learning for Exoplanet Transit Classification

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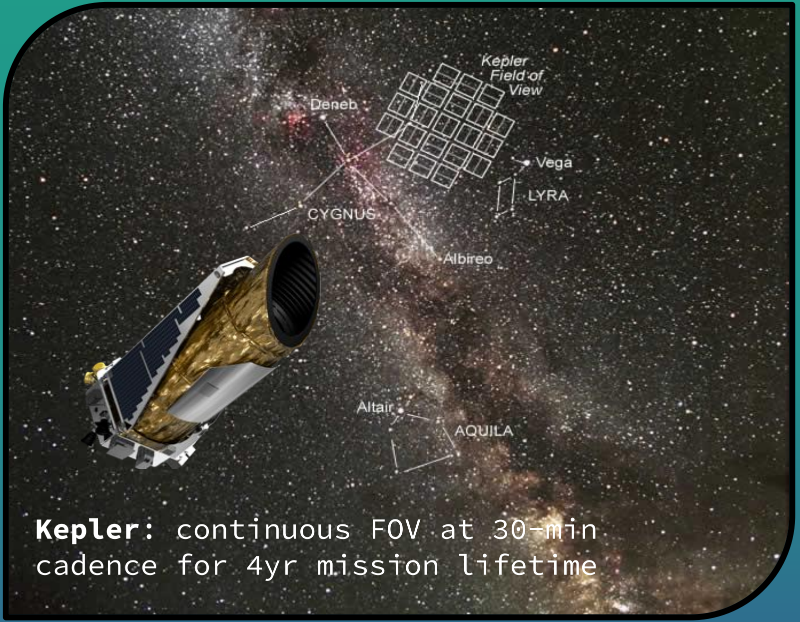
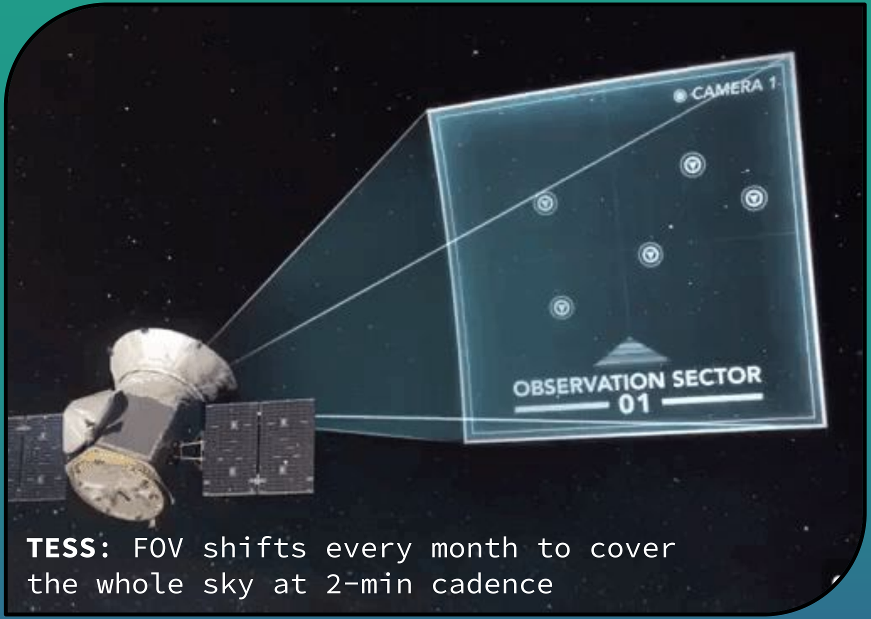
Team Mentors:

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

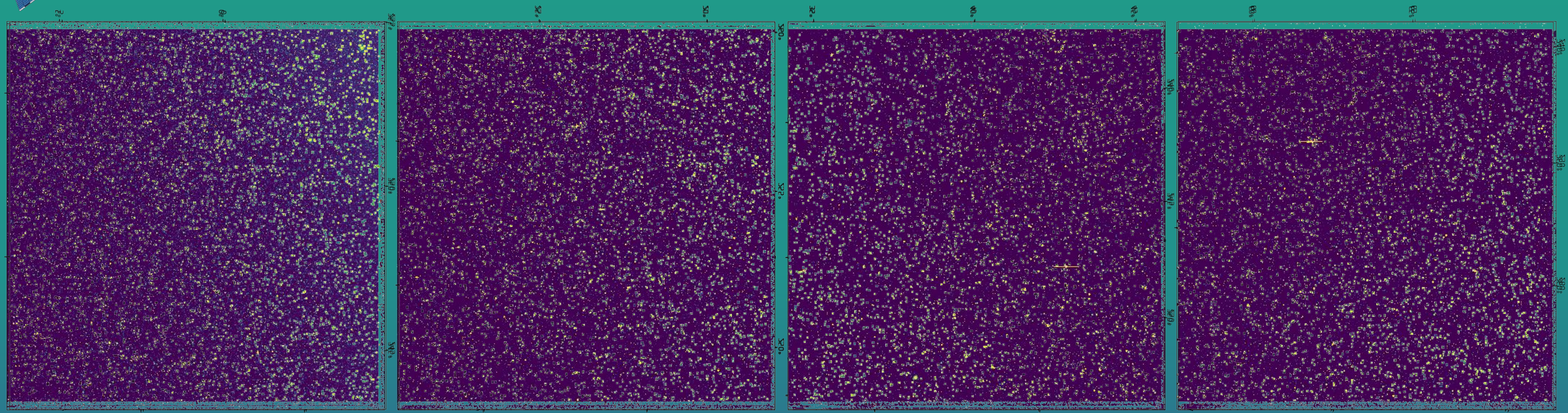
The problem:
From raw data to planets



Kepler: continuous FOV at 30-min cadence for 4yr mission lifetime



TESS: FOV shifts every month to cover the whole sky at 2-min cadence

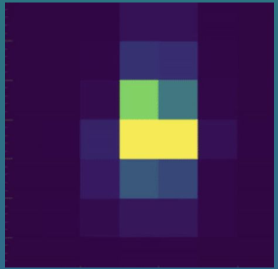


“Postage stamps” for target stars

Typical Kepler/TESS Raw data

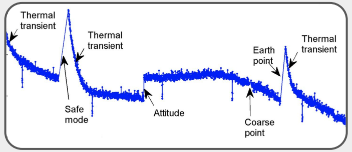
Kepler & TESS pipelines

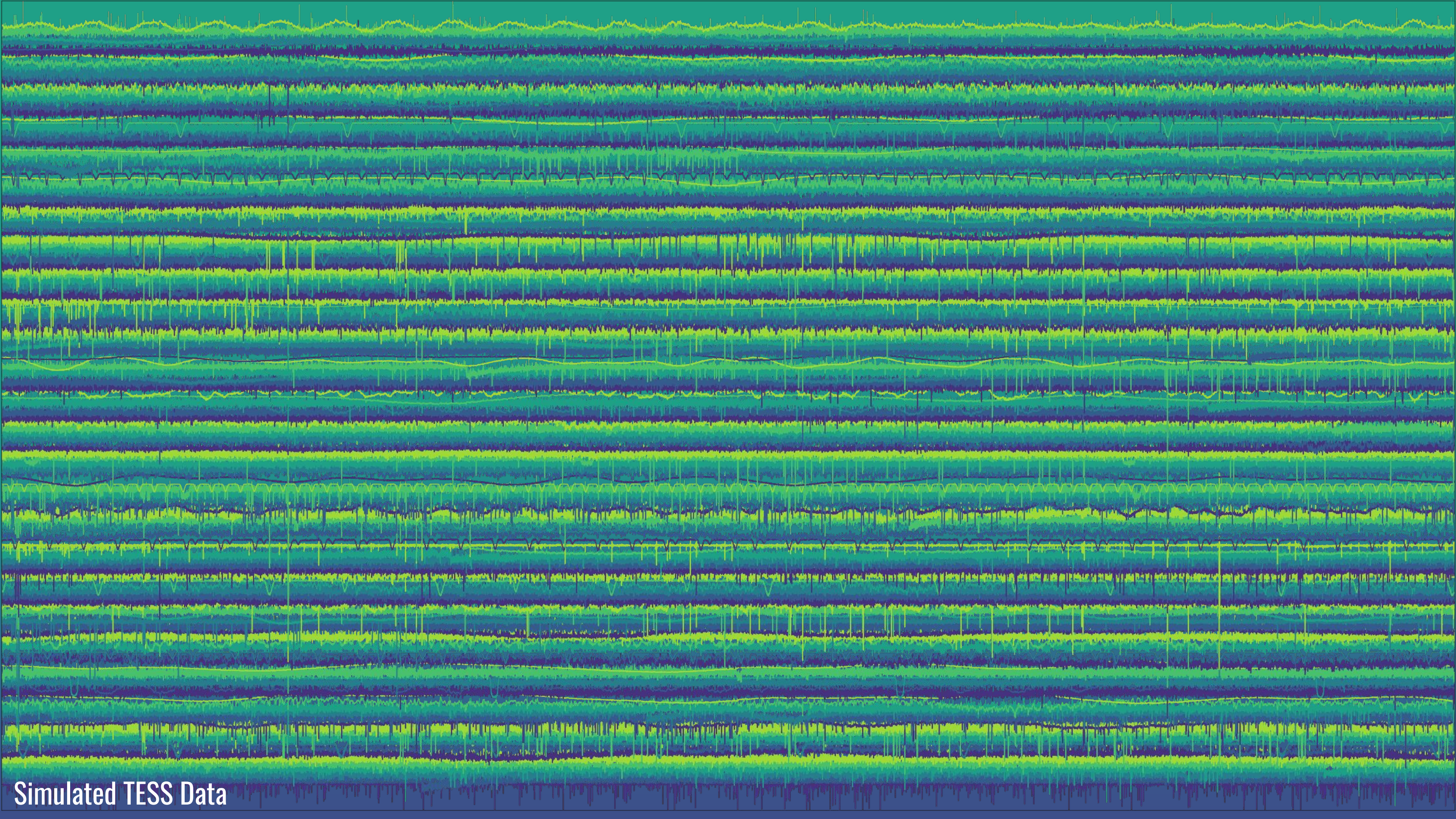
Target Pixel
File (TPF)



Smith+2012, Stumpe+2012

Aperture Photometry & Systematic Correction

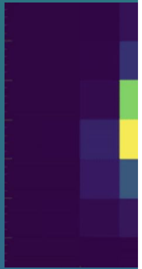


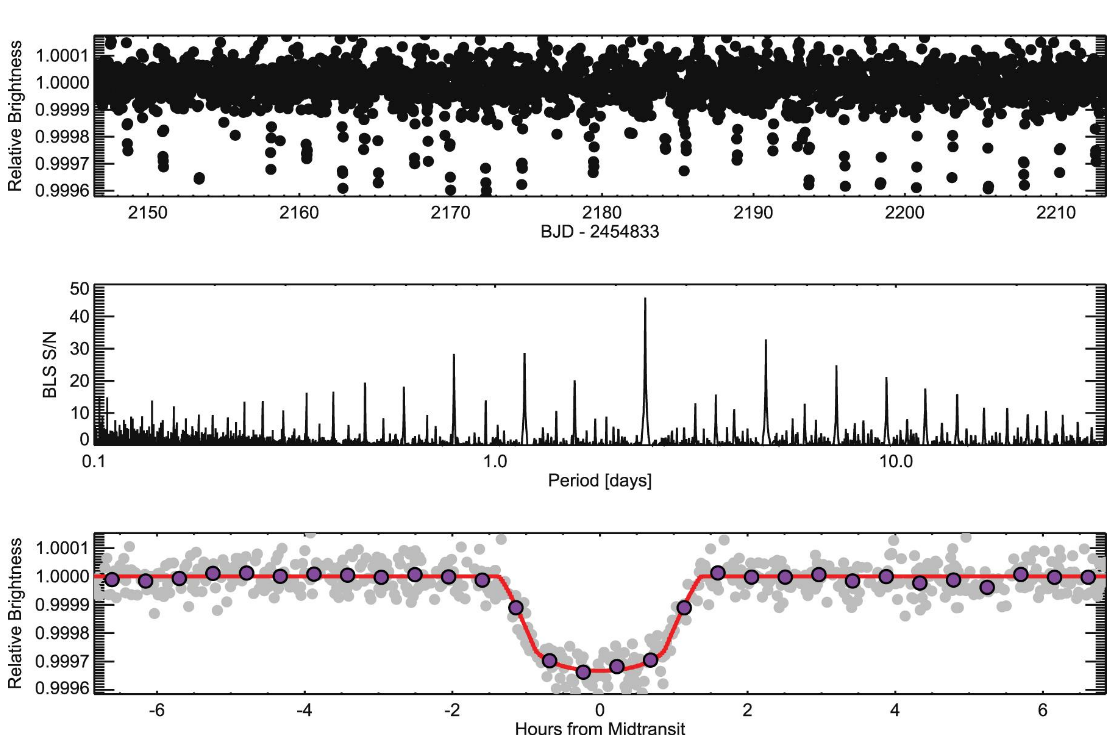

Simulated TESS Data

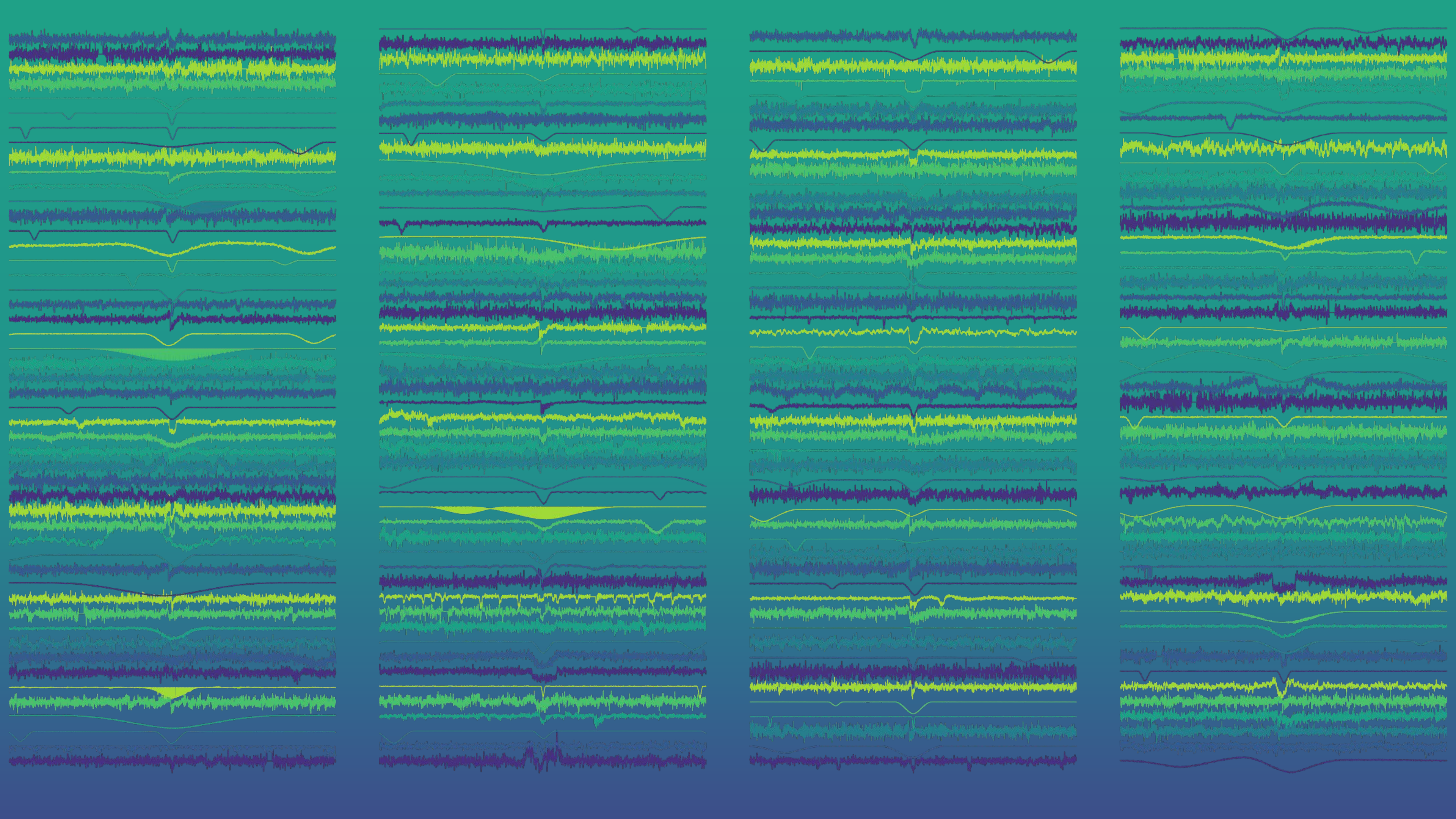
Kepler & TESS pipelines

Target
File (T

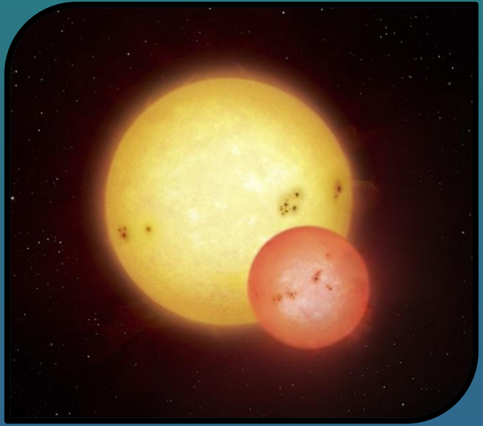
-2013



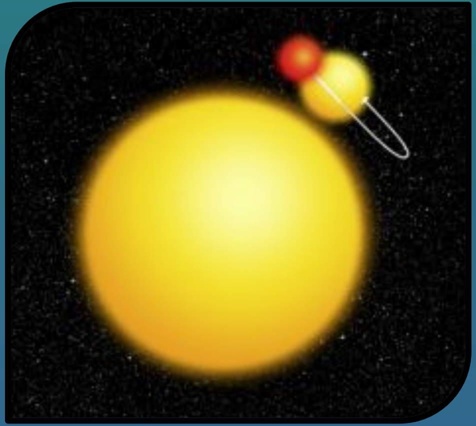


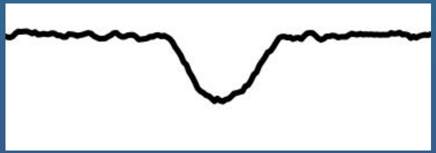


The Data: False Positives



Eclipsing
Binaries (EBs)

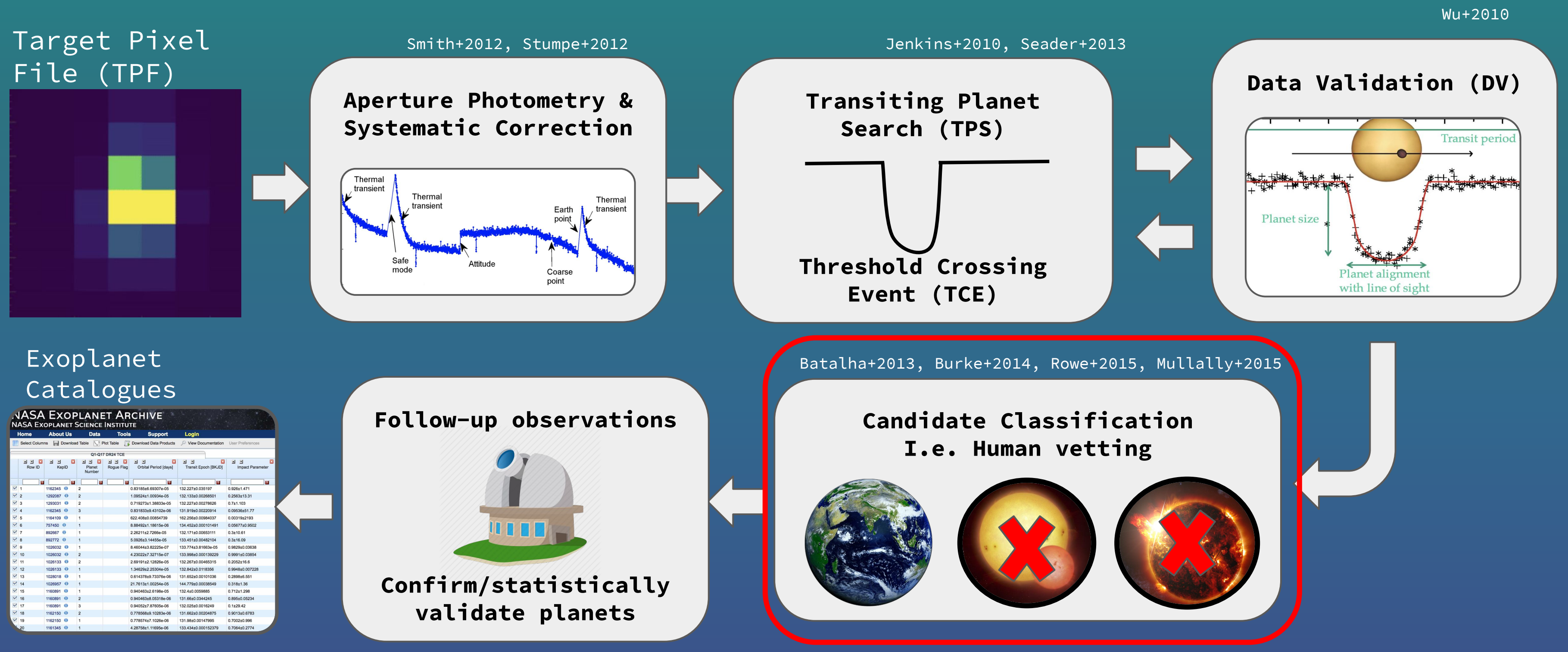




Background Eclipsing
Binaries (BEBs)

Stellar Variability /
Instrumental Noise

Kepler & TESS pipelines



Manual vetting

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

Can a machine do better?

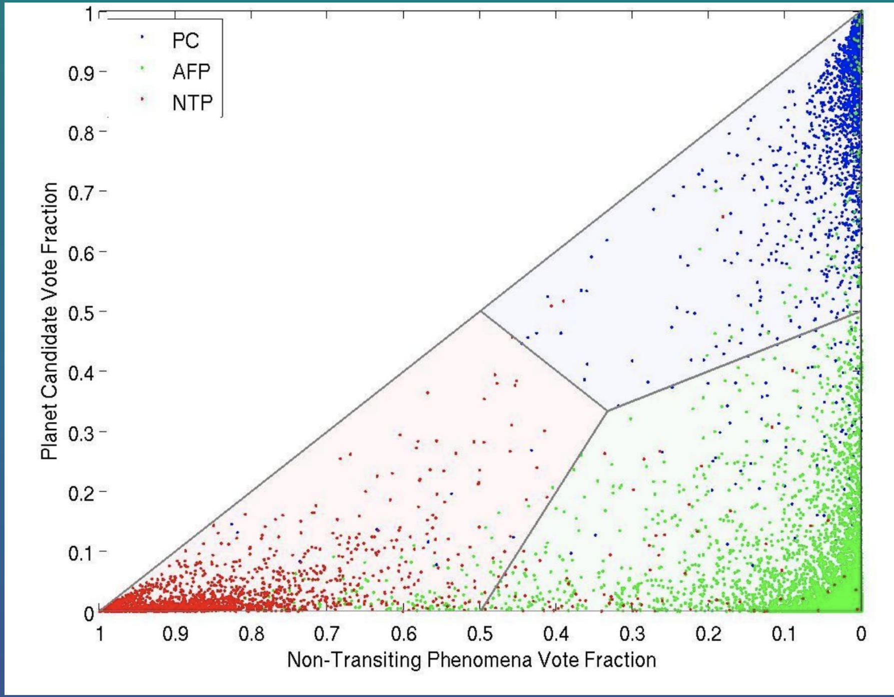
Autovetter - Random Forests

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

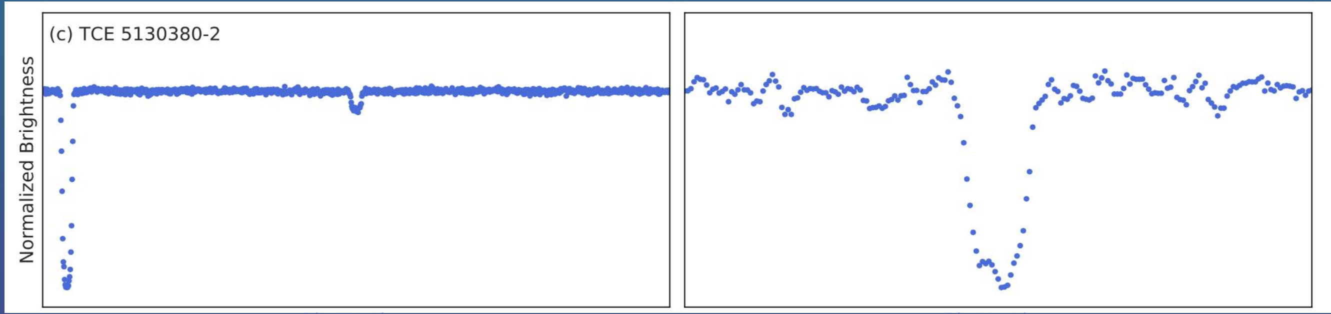
94.15% precision & 97.2% average precision (on human-labelled data)

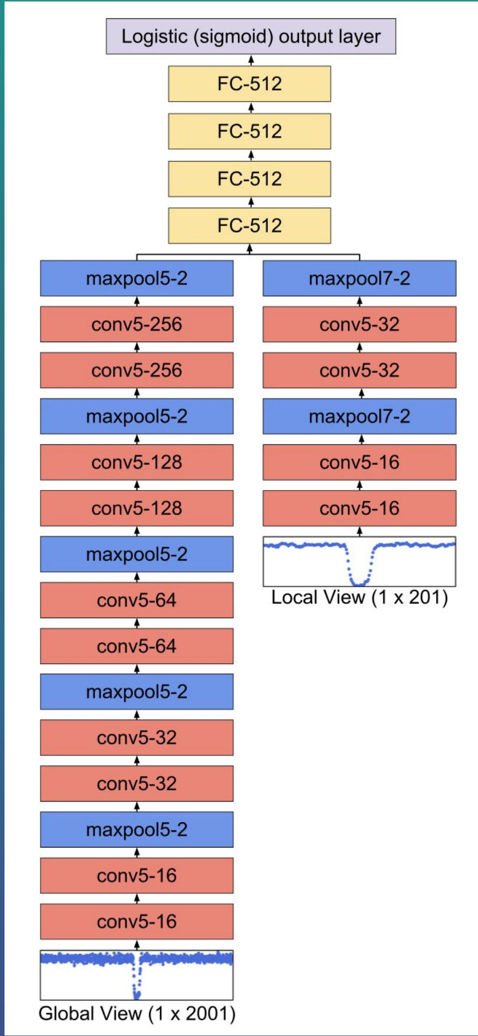


Shallue & Vanderburg 2018

Astronet

- 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 a classification in the range [0,1]





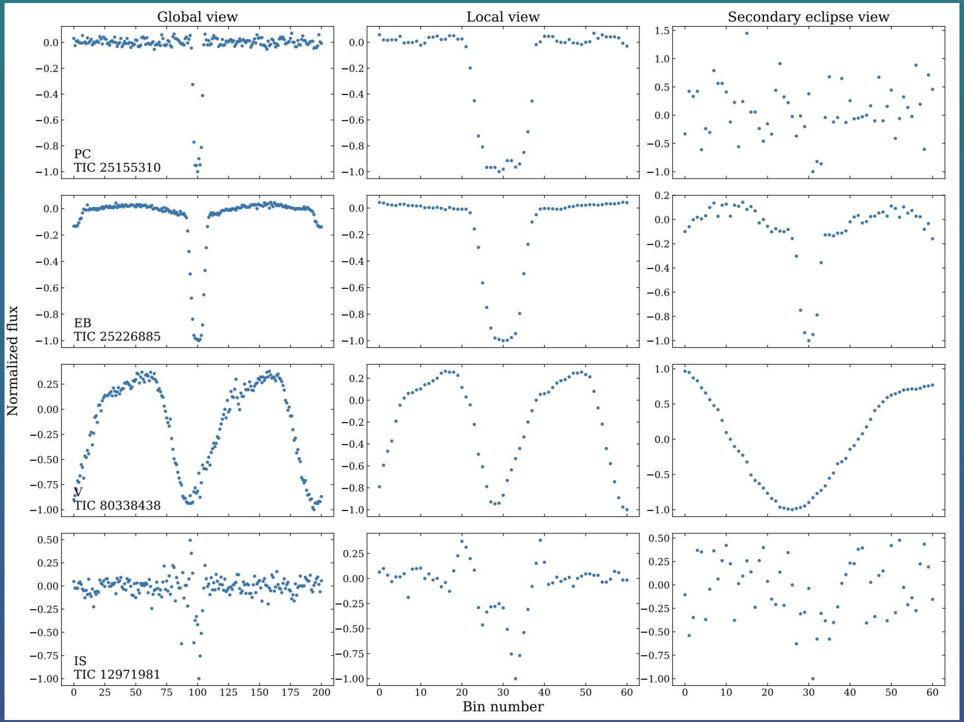
Developments on AstroNet

Application to K2 data (Dattilo et al 2019).

Application to TESS vetting: Yu et al (2019)

Included secondary eclipse region as an input.

Currently used in TESS vetting at MIT.



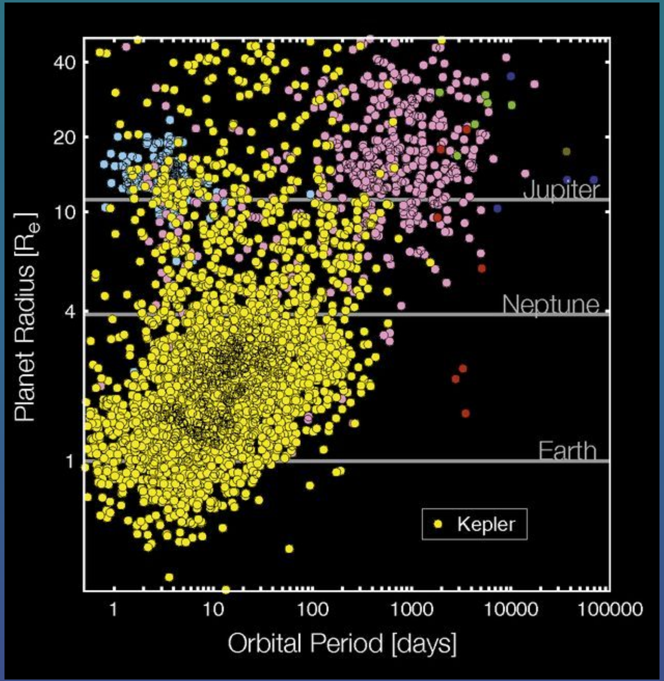
Our FDL project

“Scientific Domain Knowledge Improves Exoplanet Transit Classification with Deep Learning”, Ansdell et al (2018) https://arxiv.org/abs/1810.13434

“Rapid Classification of TESS Planet Candidates with Convolutional Neural Networks”, Osborn et al (2019) https://arxiv.org/abs/1902.08544

Kepler Input Data & Labels

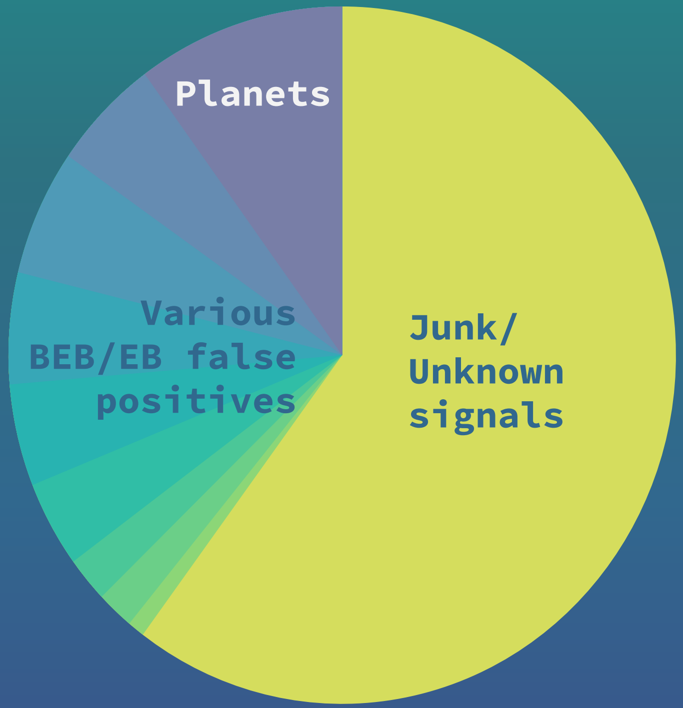
- 16,000 Threshold Crossing Events (TCEs) from Kepler DR24
- Labelled by human vetters
- ~25% planets & ~75% false positives
- Preprocessed the data following Shallue & Vanderburg:
  - Detrended lightcurve
  - Phase-folded onto TCE period
  - Binned to global & local view



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

TESS Input Data & Labels

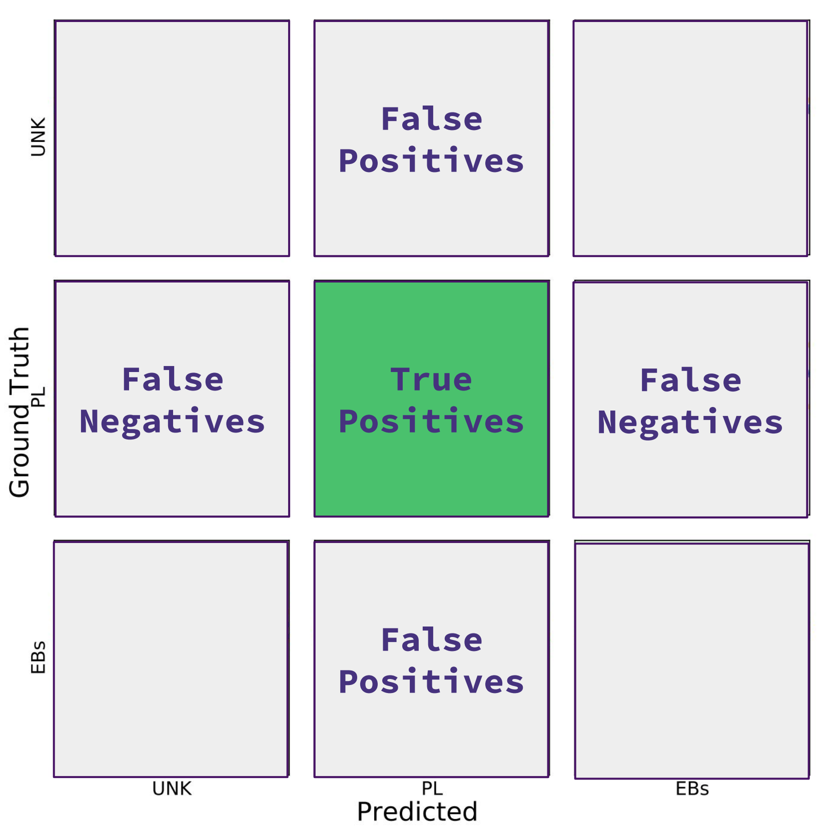
- 4 Simulated sectors - i.e. we know the exact ground-truth
- Pixel-level signal injection, processed with the TESS pipeline
- ~16,000 candidates, ~14% planets
- Preprocessed the data following Shallue & Vanderburg



Osborn, Ansdell, Ioannou, Sasdelli, et al. (2019)

Assessing Model Performance

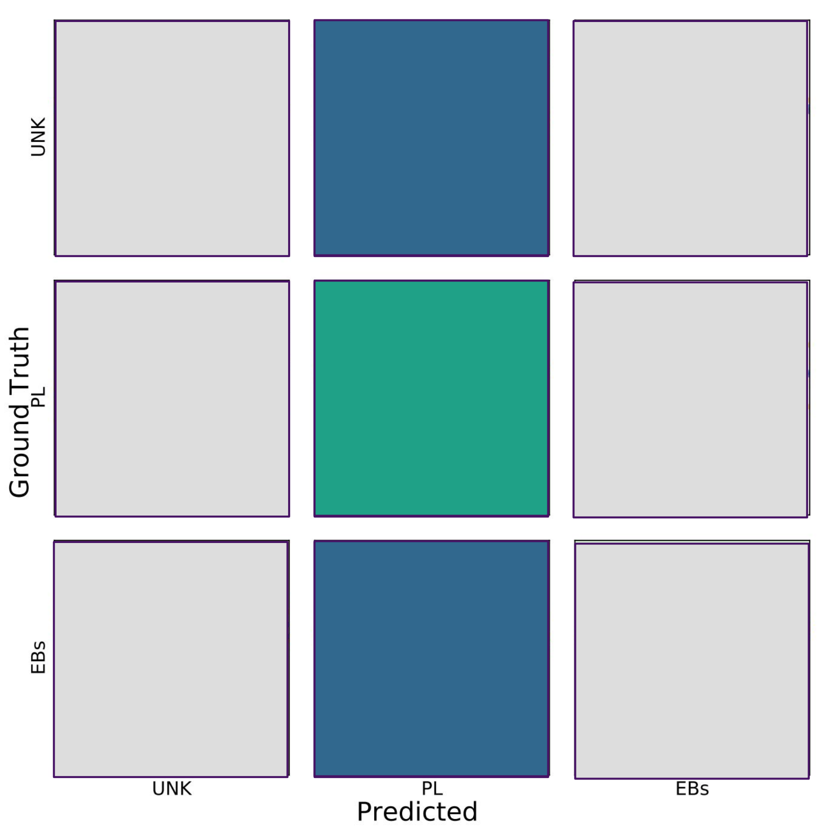
Definitions



Assessing Model Performance

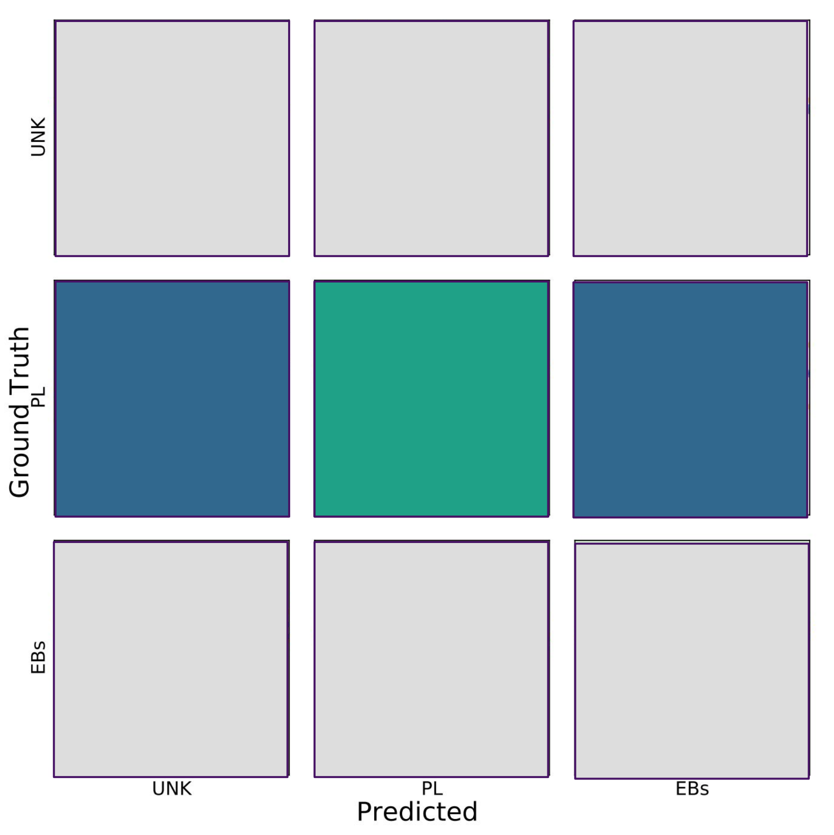
Precision

* also known as accuracy



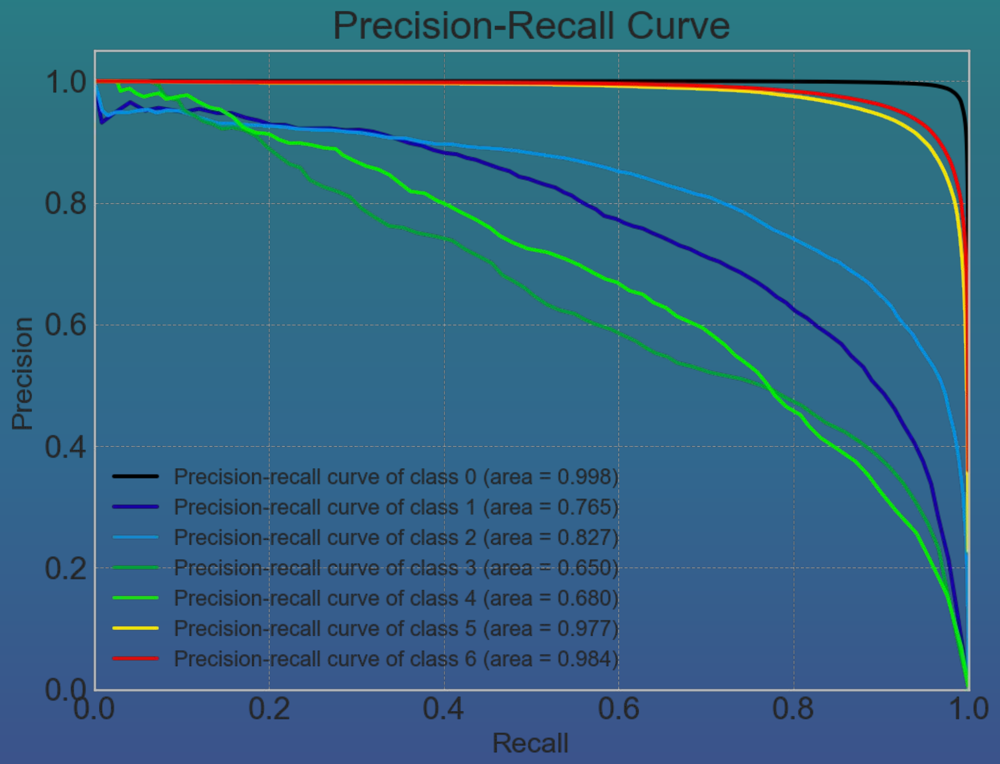
Assessing Model Performance

Recall



Assessing Model Performance

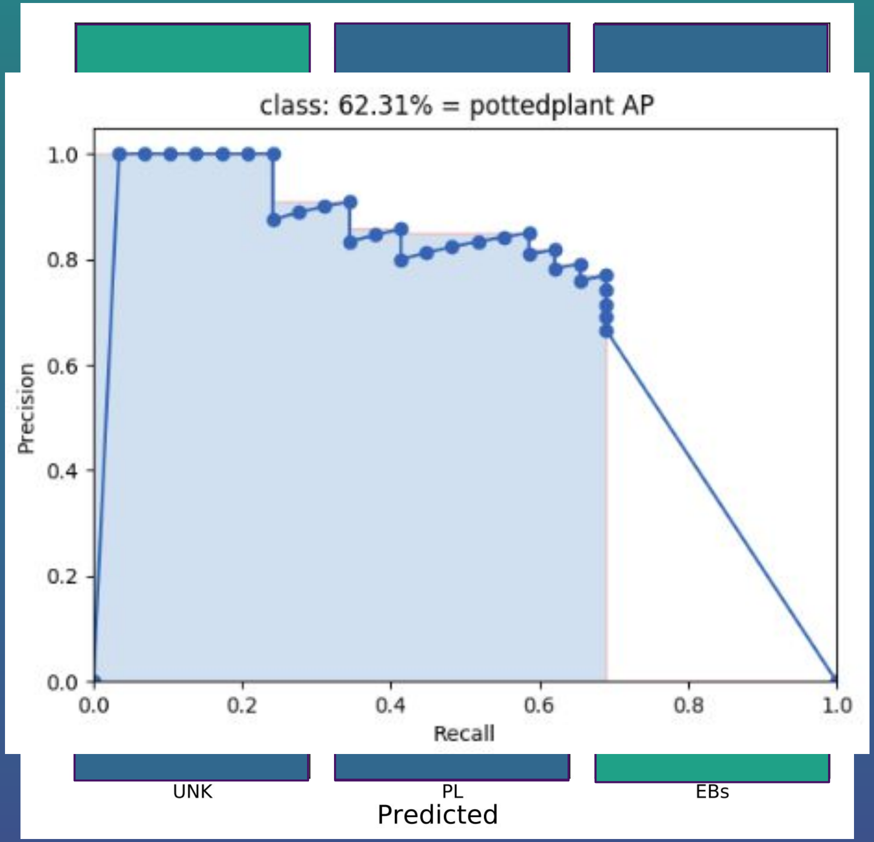
Precision-Recall Curve



Assessing Model Performance

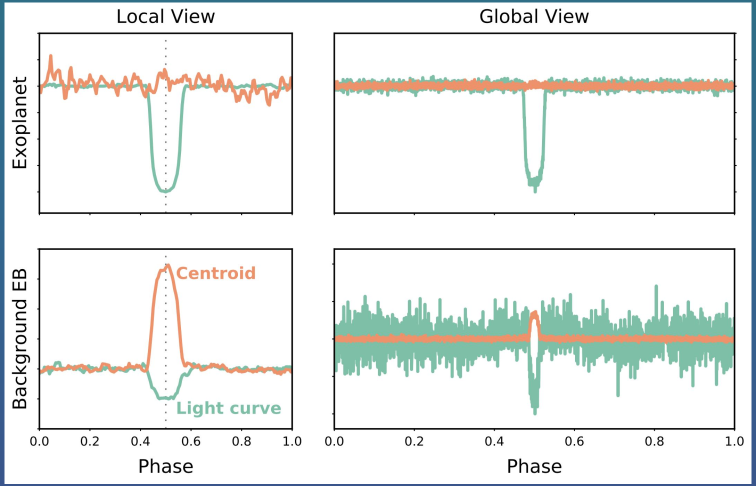
Average Precision

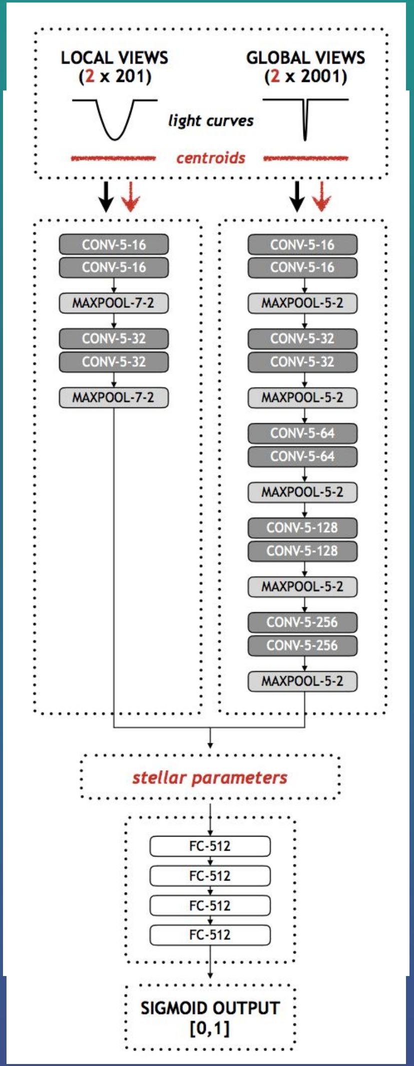
- Weighted average of precision for all classes.
- Functionally similar to Area Under Curve (AUC) for a multi-class classifier - i.e. probability a random positive sample is correctly predicted at any P-R threshold



Domain Knowledge - Centroids

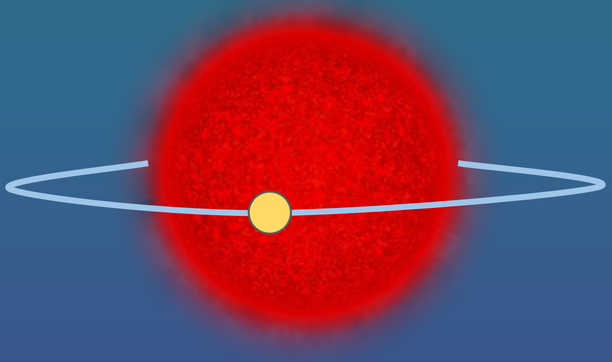
- Position of centre of light over time
- Important for identifying background EBs

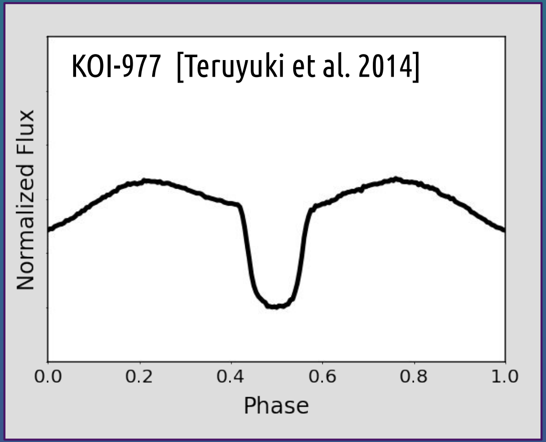


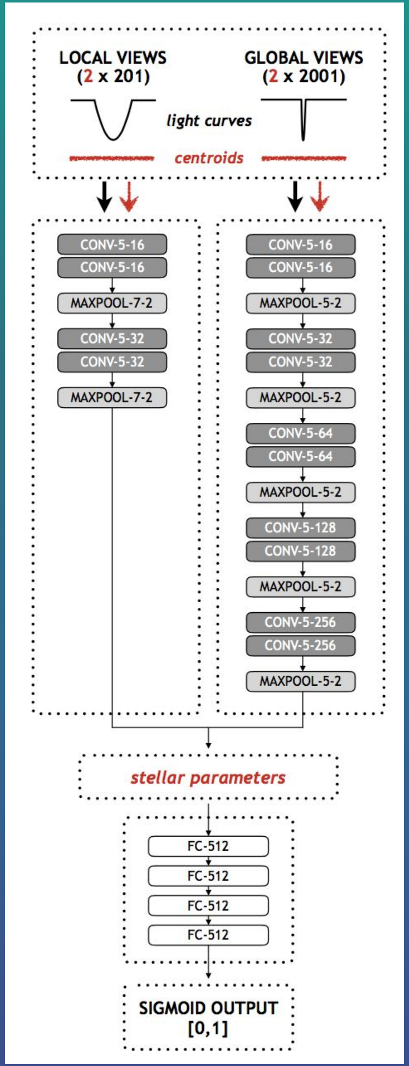


Domain Knowledge - Stellar properties

- From stellar properties catalog: mass, radius, density, logg, metallicity
- Important for identifying, e.g., giant star binaries

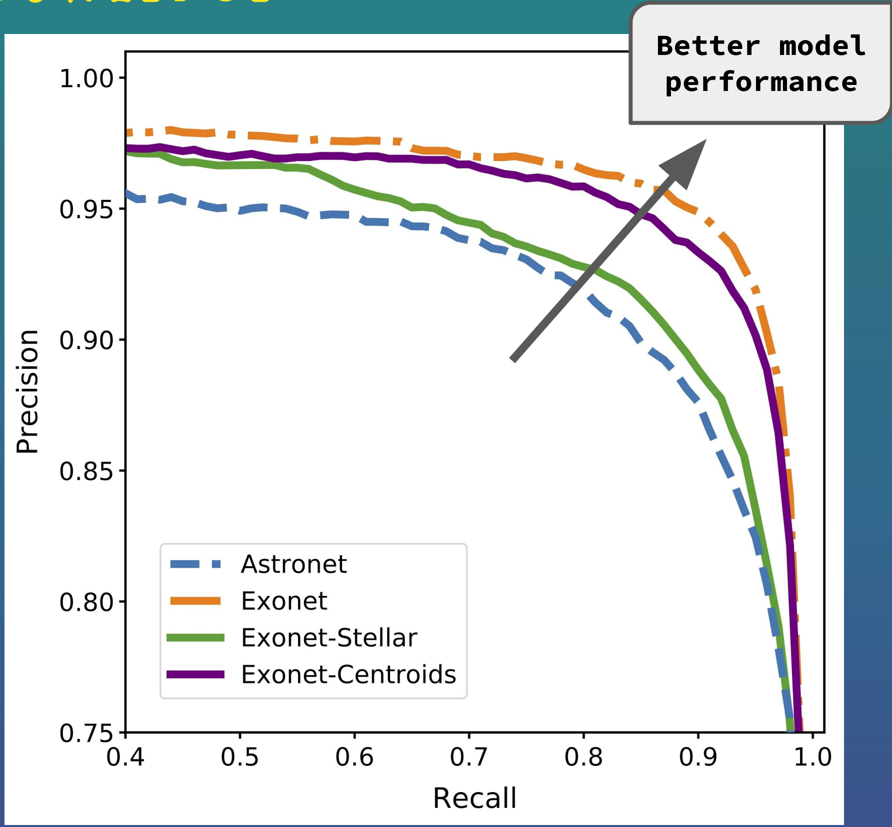






Performance With Domain Knowledge

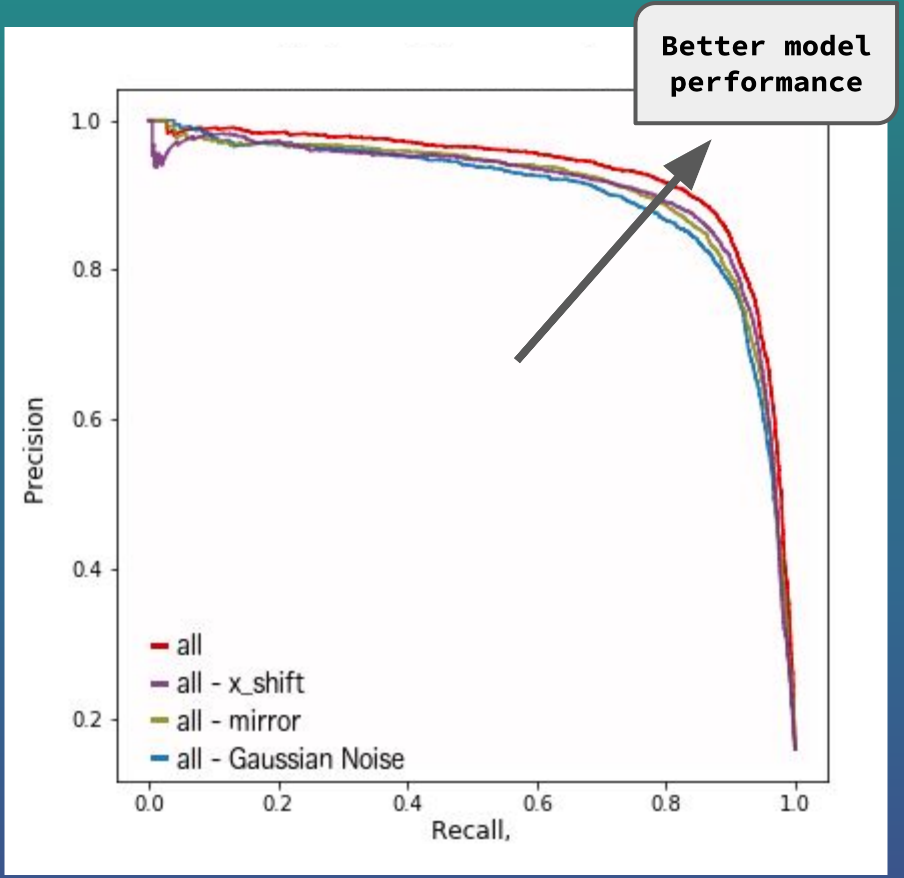
- Centroids & Stellar info both improve performance
- Also helped by cross validation & model ensembling



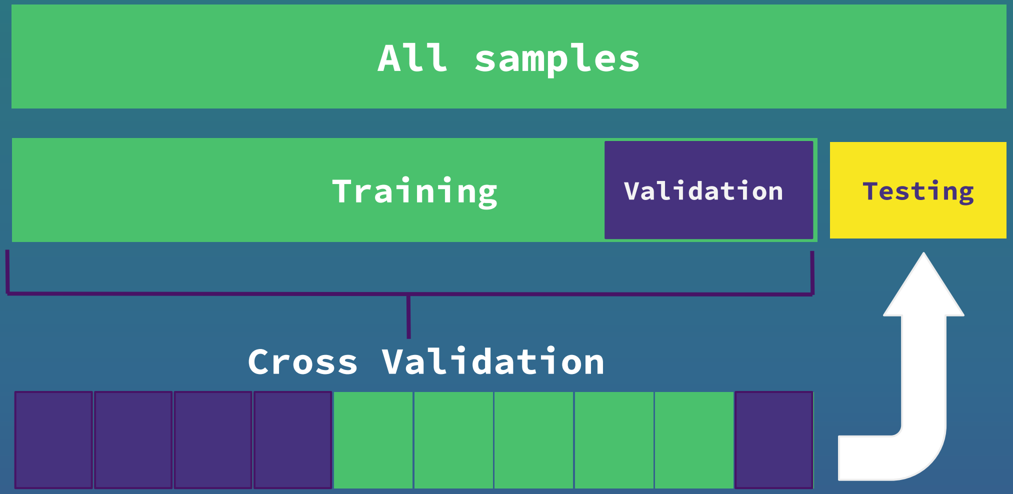
Data Augmentation

- Modify 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%



Ensembling & Cross-Validation



Ensembling / “bagging”:

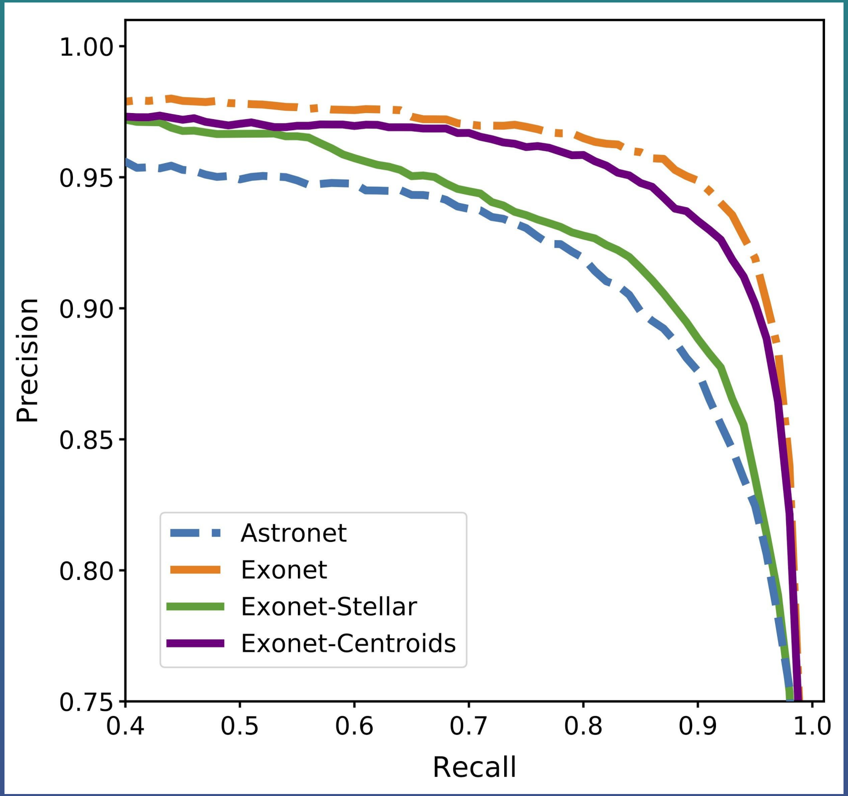
Taking average of models applied to test data

*always need test set

Multiple Validation sets = multiple trained models

Kepler Performance

- Thanks to domain knowledge, augmentation, ensembling, etc - Exonet-Kepler improves on Astronet, and is the best classifier of Kepler candidates yet.



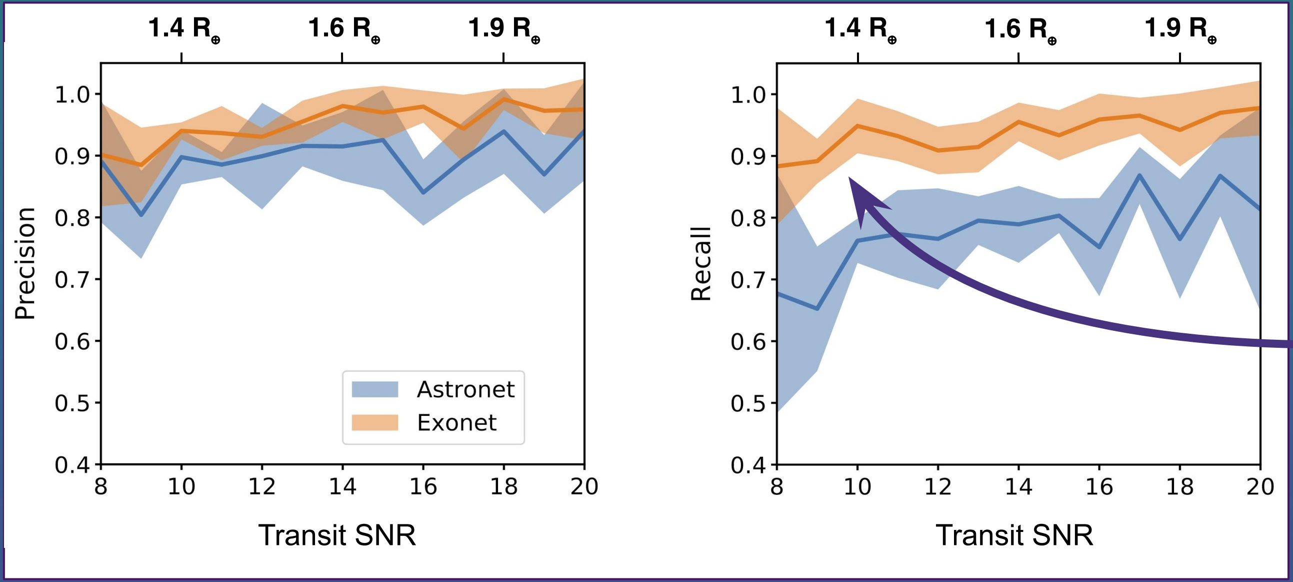
Kepler Performance

- Thanks to domain knowledge, augmentation, ensembling, etc - Exonet-Kepler improves on Astronet, and is the best classifier of Kepler candidates yet.

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

Kepler Performance

Improved Performance for Lowest SNR Transits

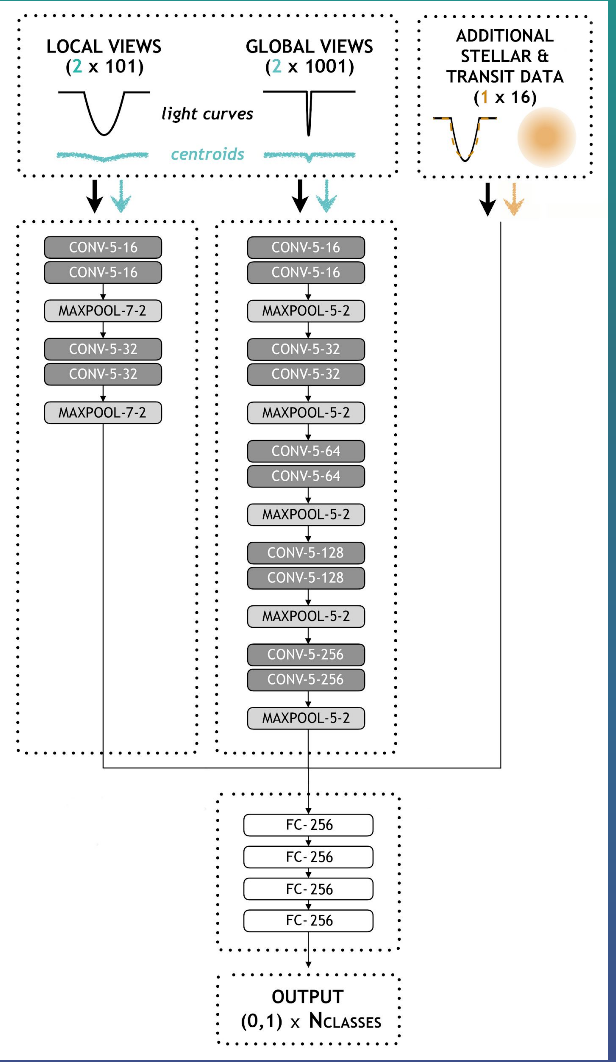


15-20% gains in recall for Earth-sized planets

Classifying TESS Data

Slightly modified from Kepler -> TESS

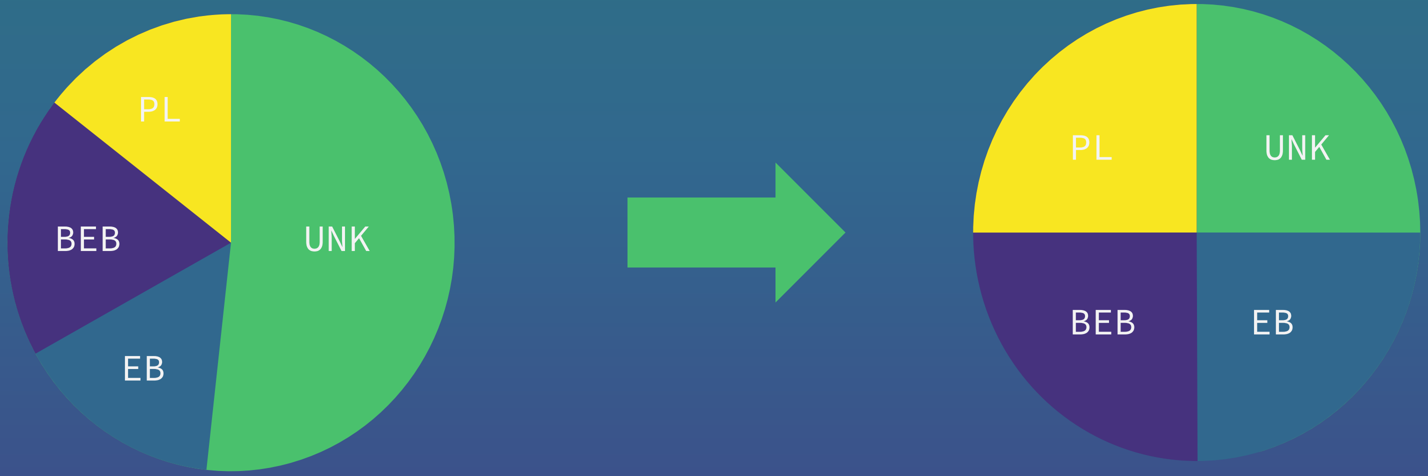
- Added additional transit-derived information
- Reduced bins from 2001 to 1001
- Used multi-class modelling



Osborn, Ansdell, Ioannou, Sasdelli, et al. (2019)

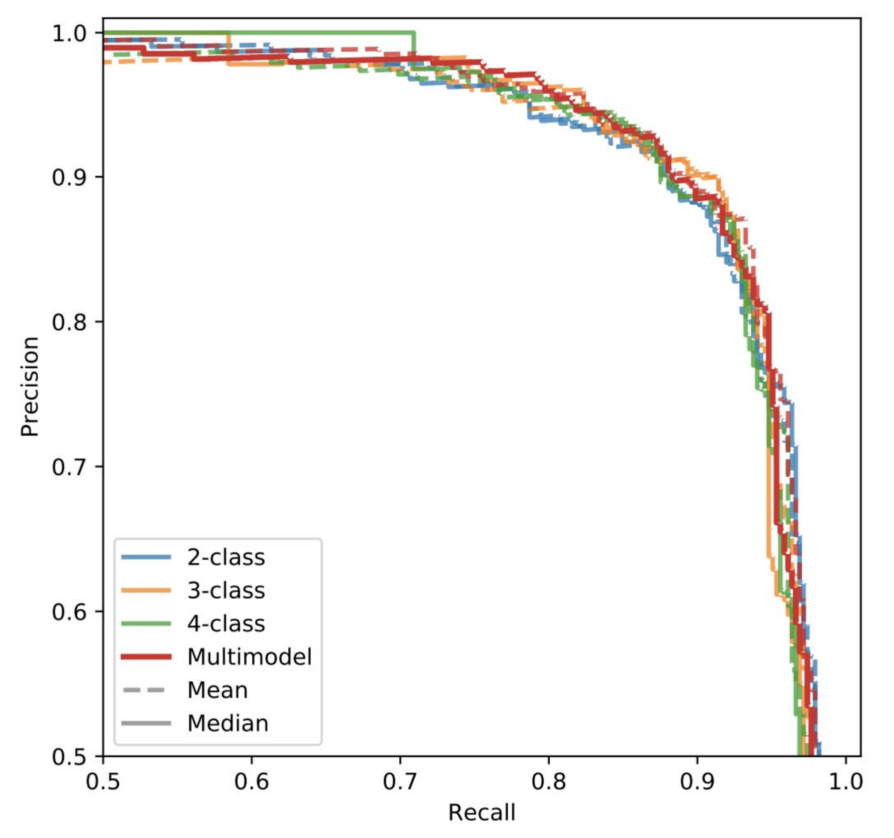
Balanced Batch Sampling

- Models tend to predict the majority class in unbalanced data
- Re-balancing means that each epoch sees same number of samples from each - helps training

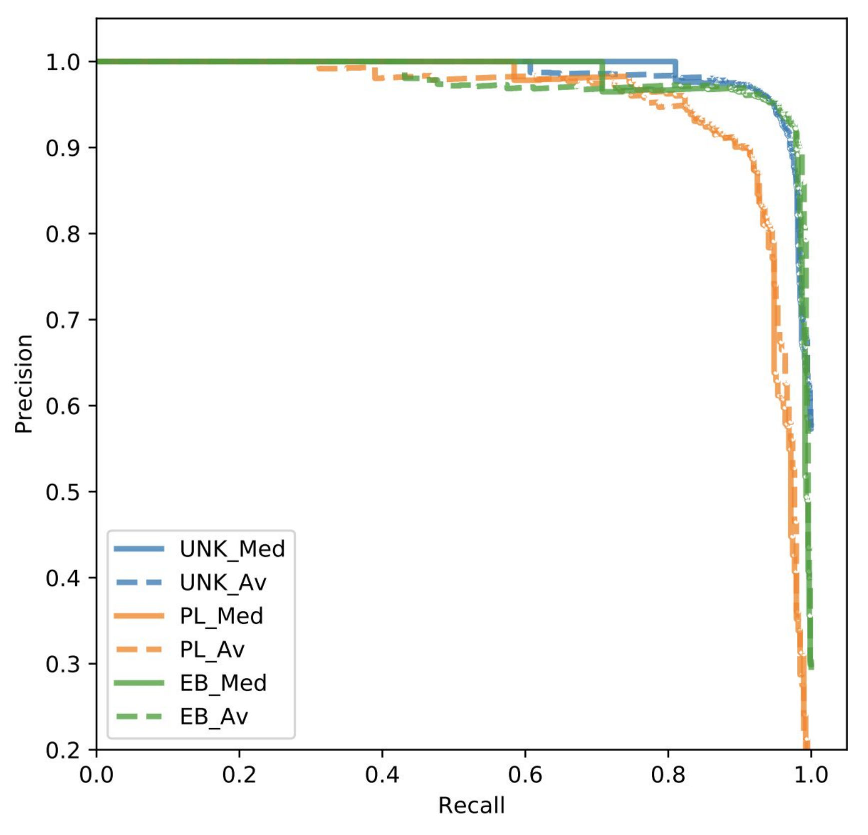


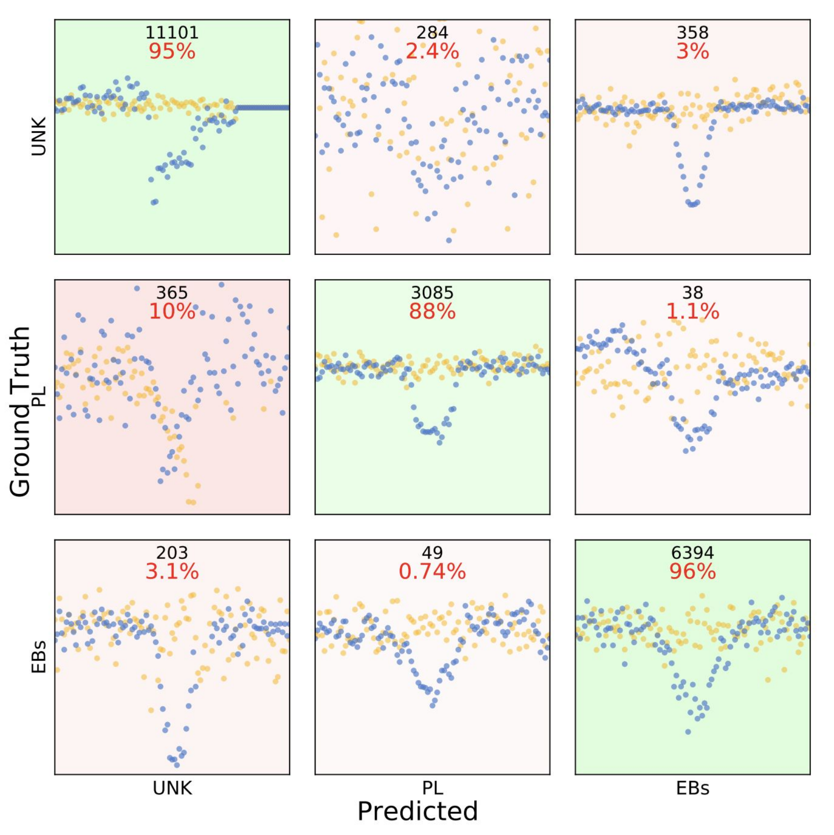
Performance on TESS Simulations

		Planet Precision	Planet Recall	Av. Precision
	Planets	**90.4**	**90.1**	**95.6**
	EBs	95.1	95.1	96.9
	Unknown	94.8	94.9	97.7

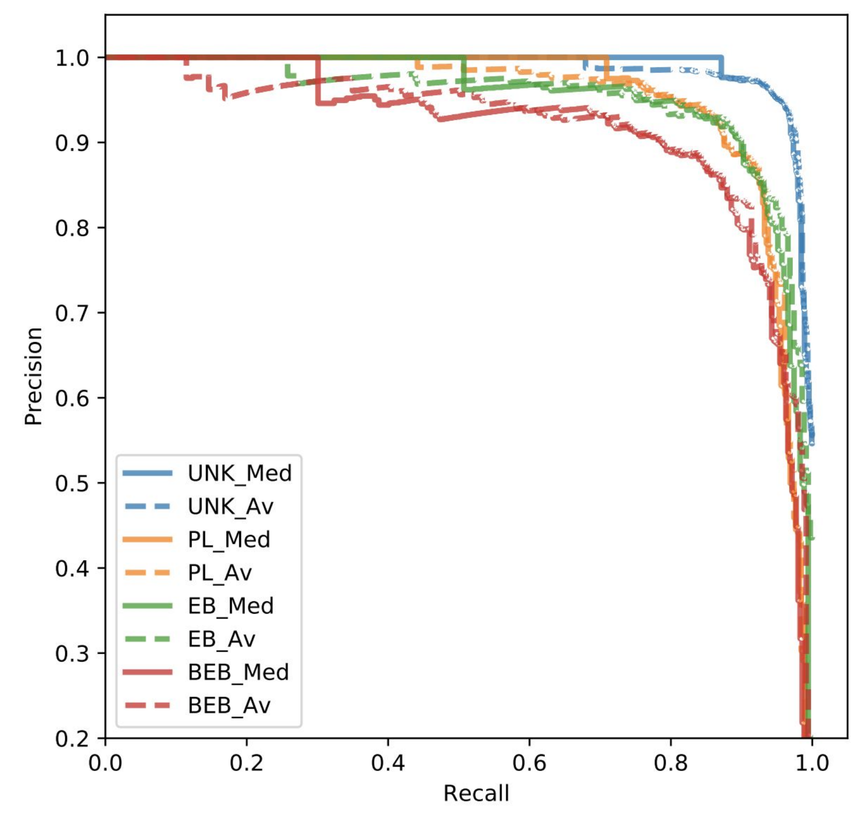


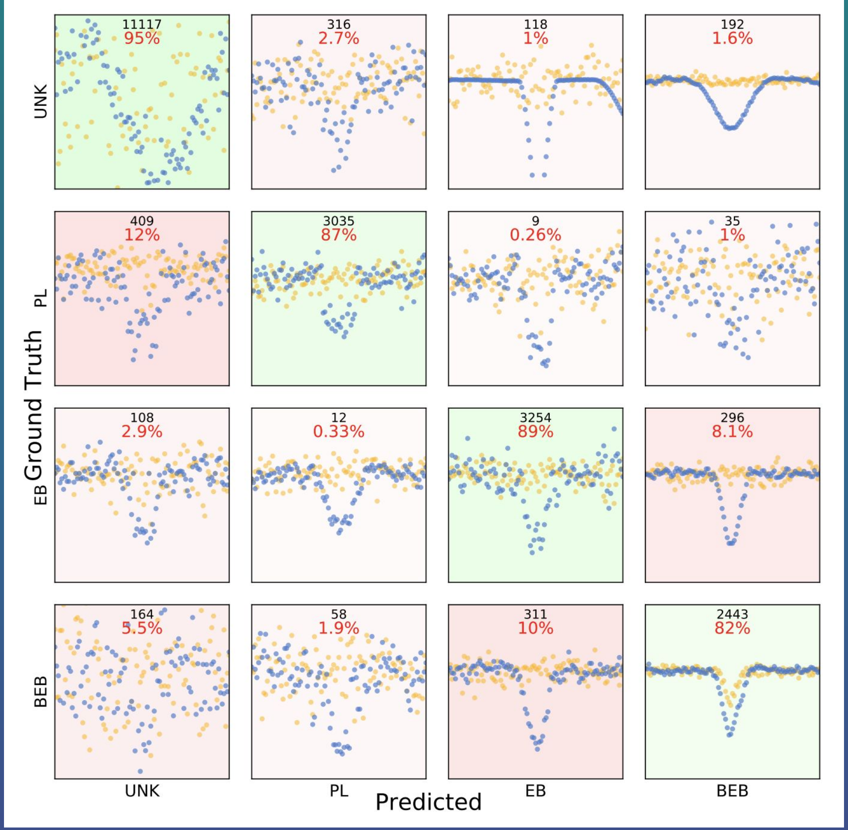
3-class model





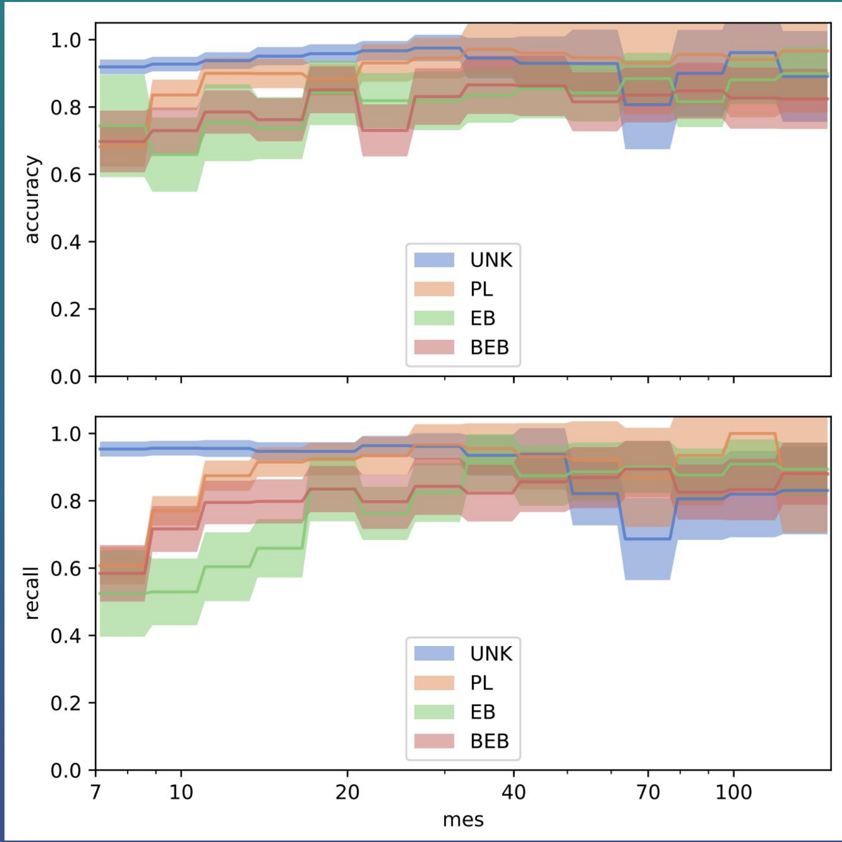
4-CLASS MODEL





Performance as a function of SNR

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

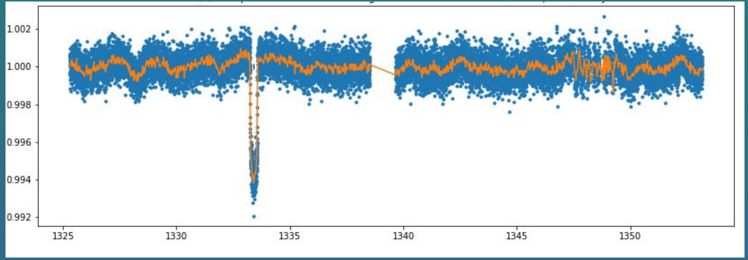


Kepler-TESS Comparison

	Precision on planets
Kepler	98.5%
TESS	90.3%

Why?

A Monotransit flagged as periodic in real TESS data.



- Labels: Human vetting vs. Simulated ground truth
- “Near misses” - 196 “false positives” are planets
  - 44% from monotransits
  - 25% from period confusion
- Including “near misses” - planet precision from 90.3% to 95.1%

Application to real TESS data

Fast! Much quicker 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

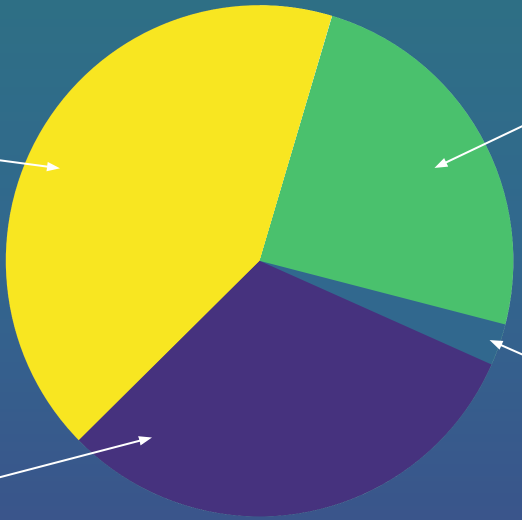
- Simulated systematic noise ≠ real noise
- Injection populations ≠ real populations
- No “ground truth” to make comparisons

Application to real TESS data

All TOIs in Sectors 1-5

Recall of only 61% on TOIs

Our model thinks 30% are noise...



14 we suggest are EBs

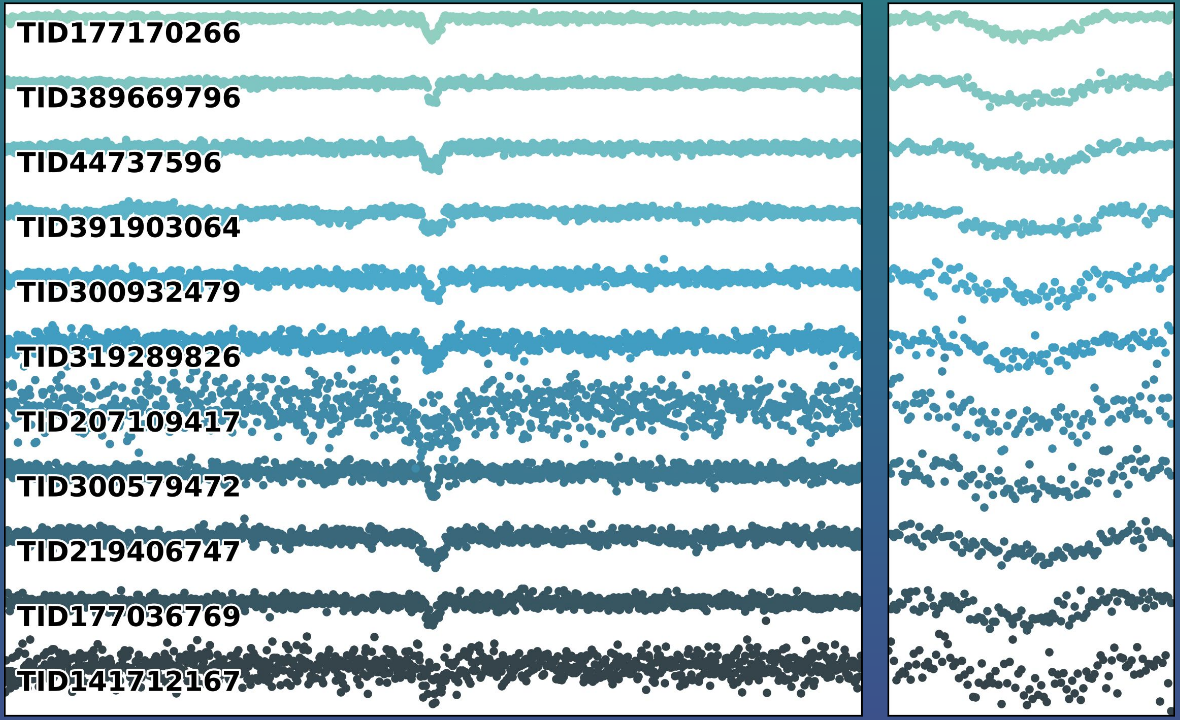
TOIs not in our data sample

New predicted planets

>100 new candidates from model predictions

Problems:

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



Conclusion

- Machine Learning using “domain knowledge” enables fast & more accurate classification of transiting planet candidate vetting.
- Kepler-ExoNet is the best-performing model yet tested, with a precision on Kepler candidates of 97.5%
- TESS-ExoNet also performs well, achieving 95% planet precision on simulated training set.
- However, models trained on simulations don’t (yet) perform as well on real data!
- We have identified promising new candidates missed by manual vetters.

Thanks!
Any Questions?

Hugh Osborn

@exohugh

Classification with Machine Learning

Classes >
Samples ^
< Ground truth
Bill
Claire
Frans
Alfred
Herman
Maria
Alex
Max
Anne
Philip
Tom
Richard
Robert
©1996 M.B. Co.

Decision Tree Classifier

Sample to be classified

Are they an astronomer?

Yes → Do they have a beard? | No

Do they have a beard?

Yes → Hair longer than 5cm? | No

Hair longer than 5cm?

Yes → German? | No

German?

Yes → Dan | No → (Hugh, etc)

^ Predicted class

Decision Tree Classifier

Sample to be classified

Does it have a secondary eclipse

Yes

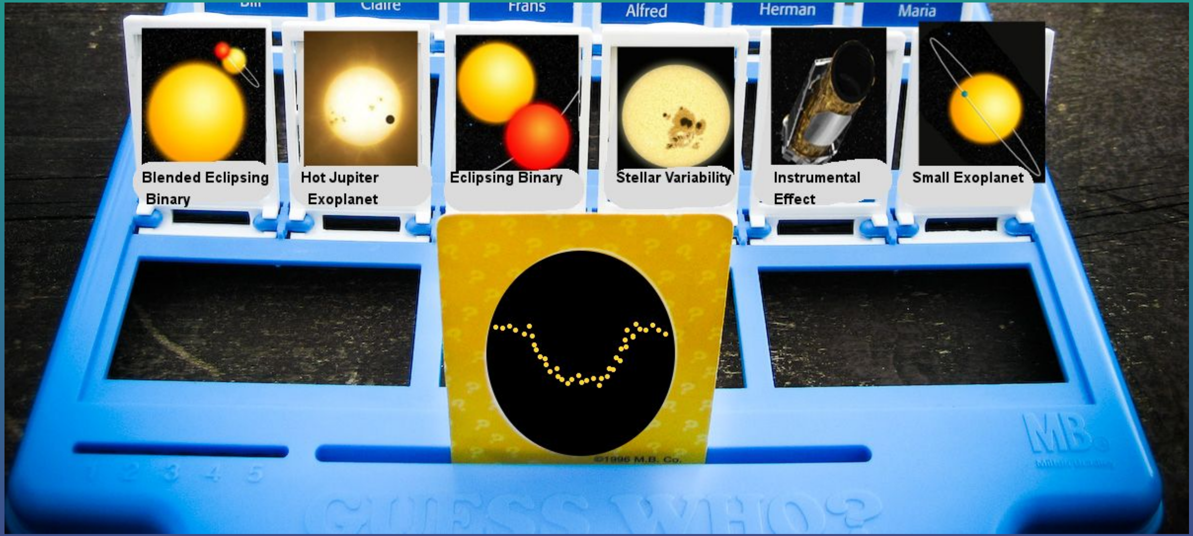
No

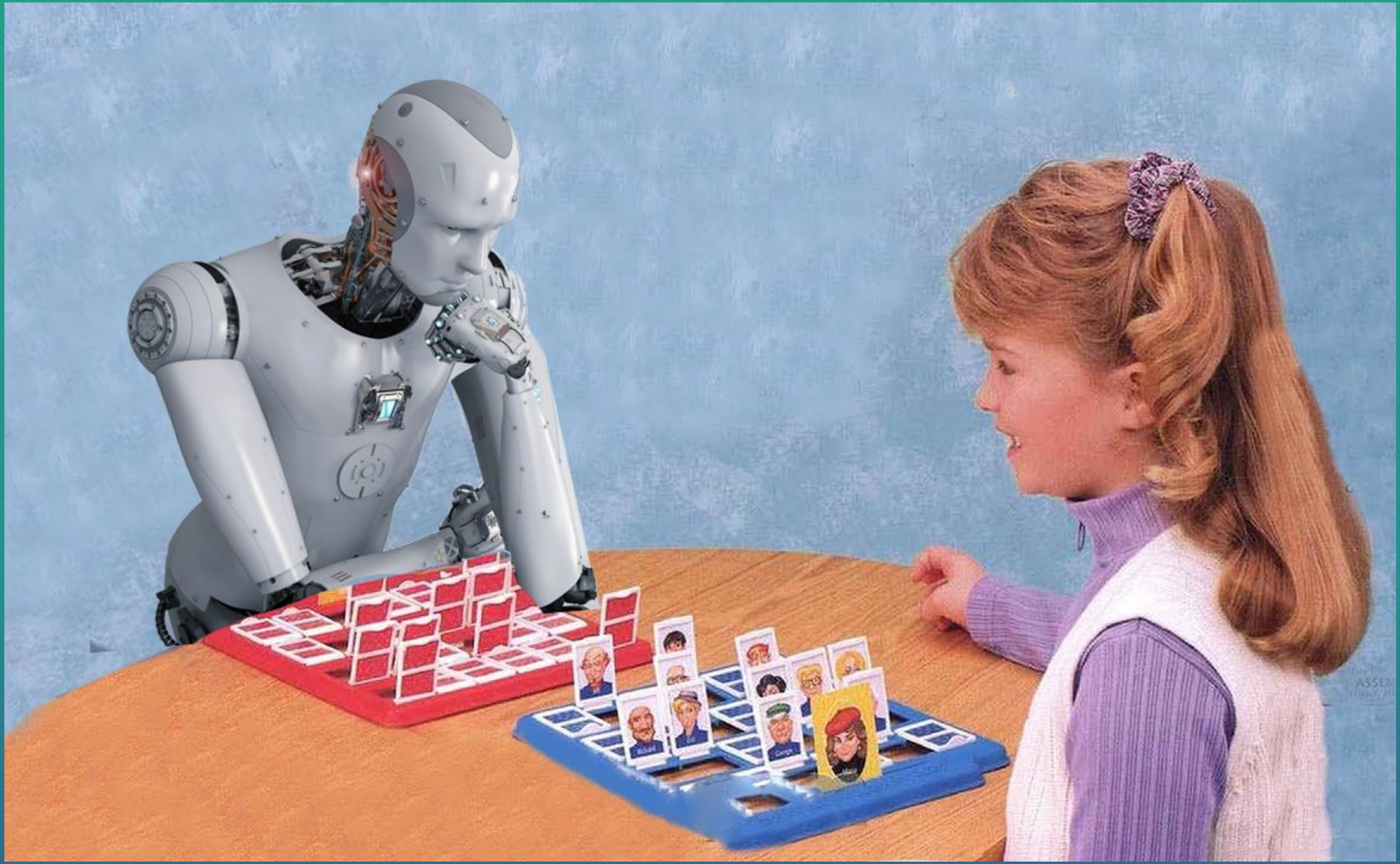
Is the modelled albedo >1

Yes

No

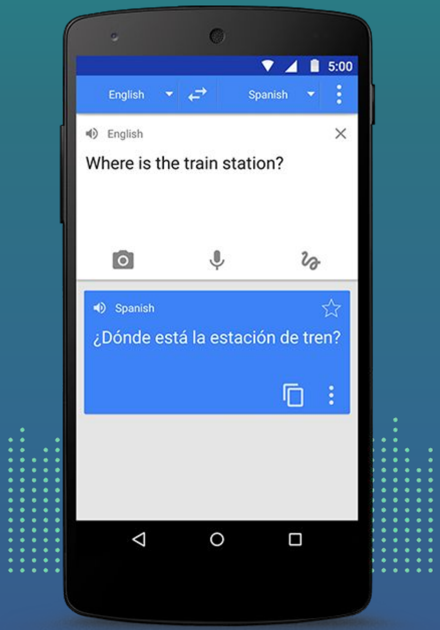
Eclipsing Binary

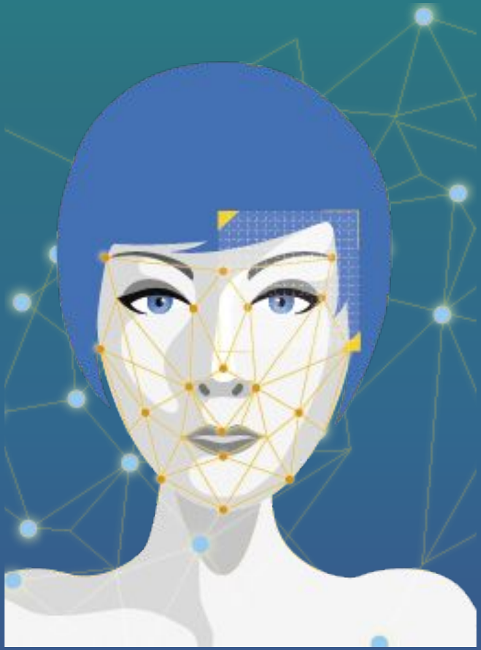


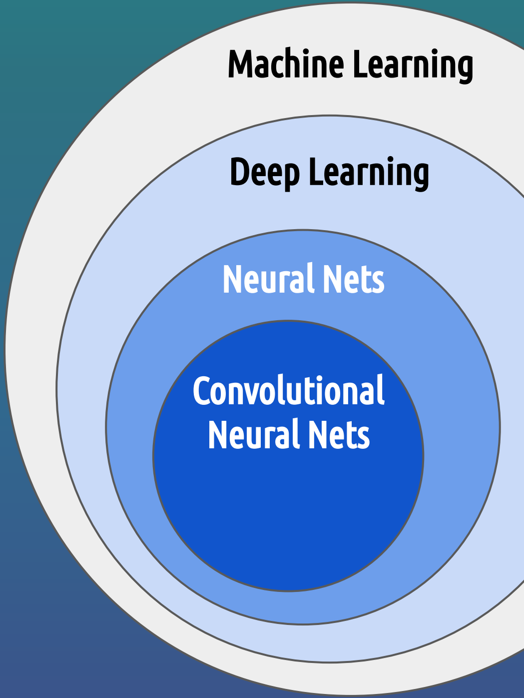


How can we classify with minimal human processing?
With Machine Learning

Machine Learning







Translation

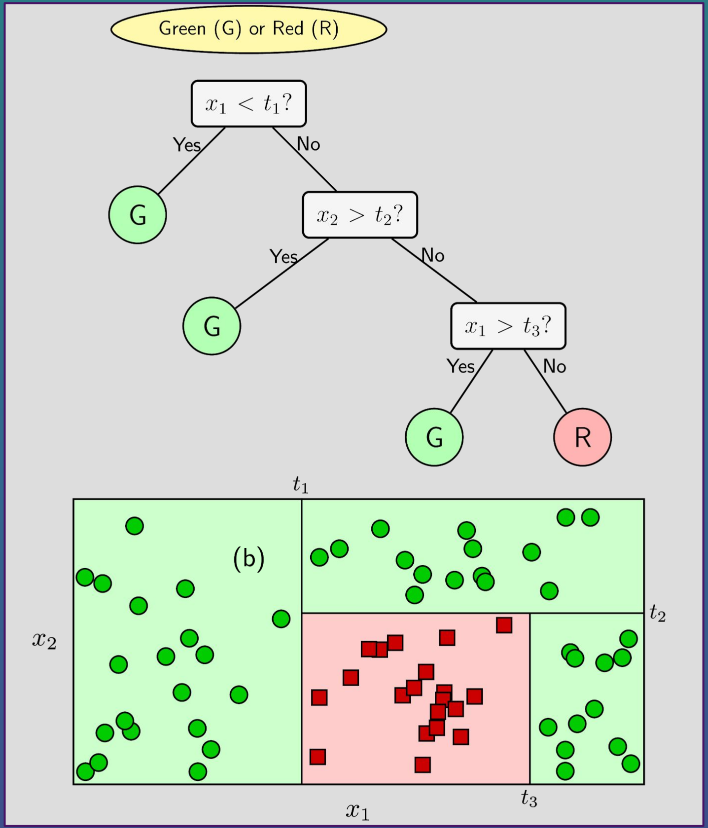
Self-driving cars

Decision Trees

- 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



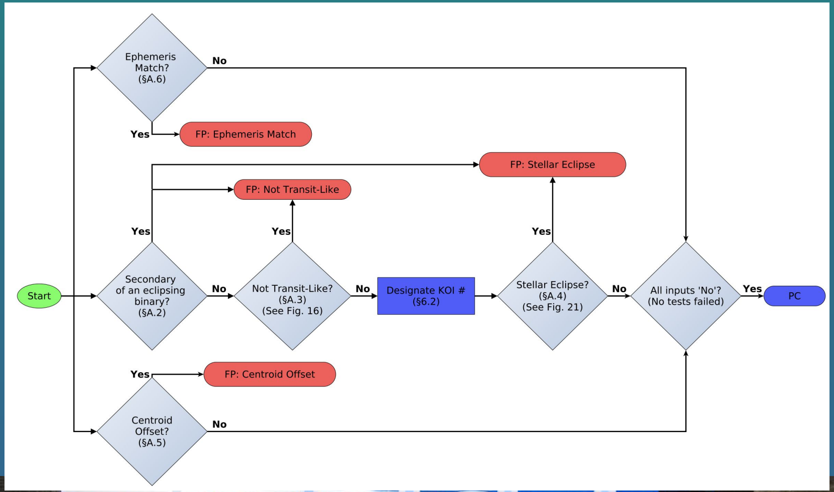
Robovetter - Decision Tree

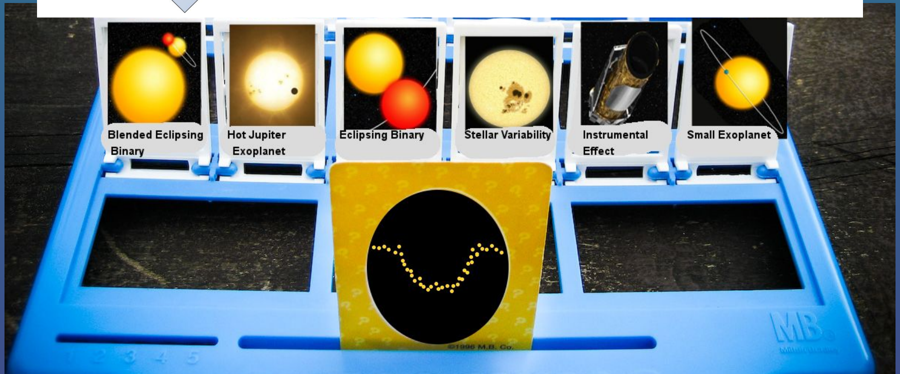
"Robovetter" – Thompson et al 2017.

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

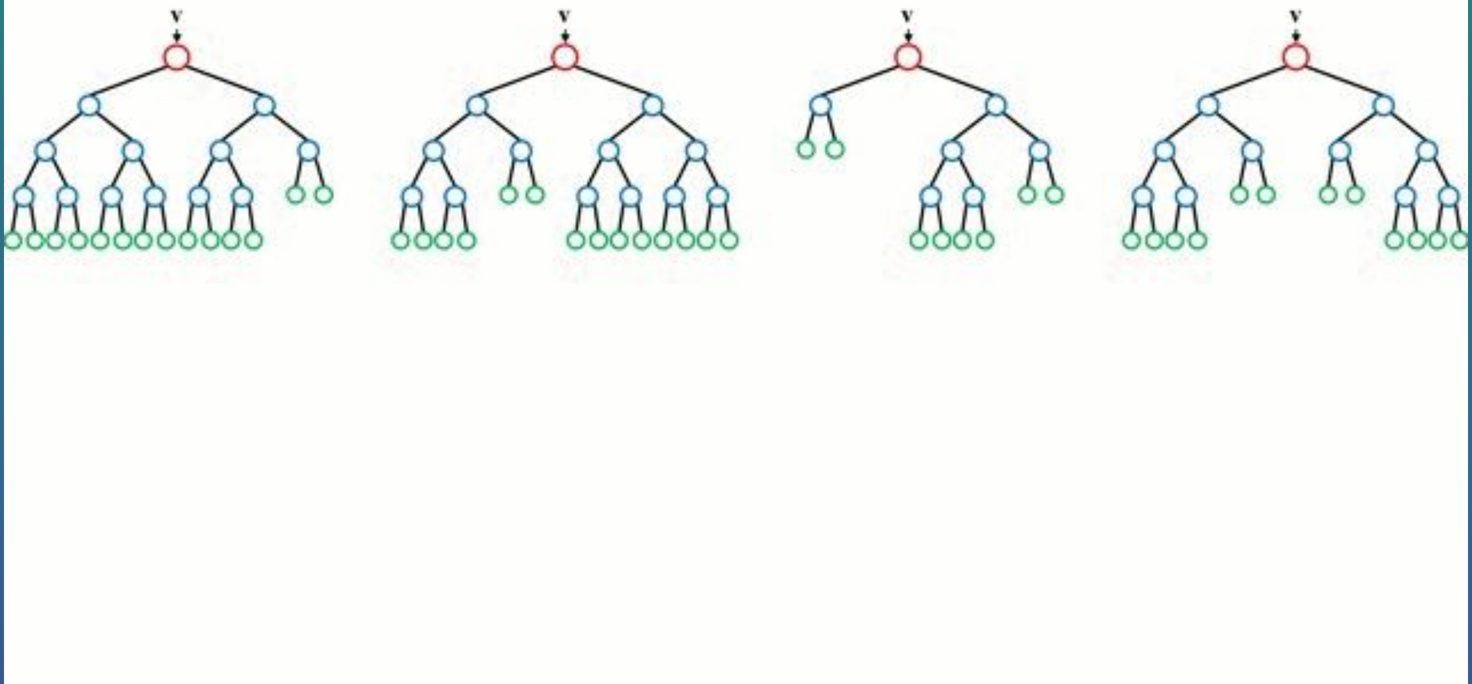
Used features processed from lightcurve.

Achieved a recall of around 80% on injected data.





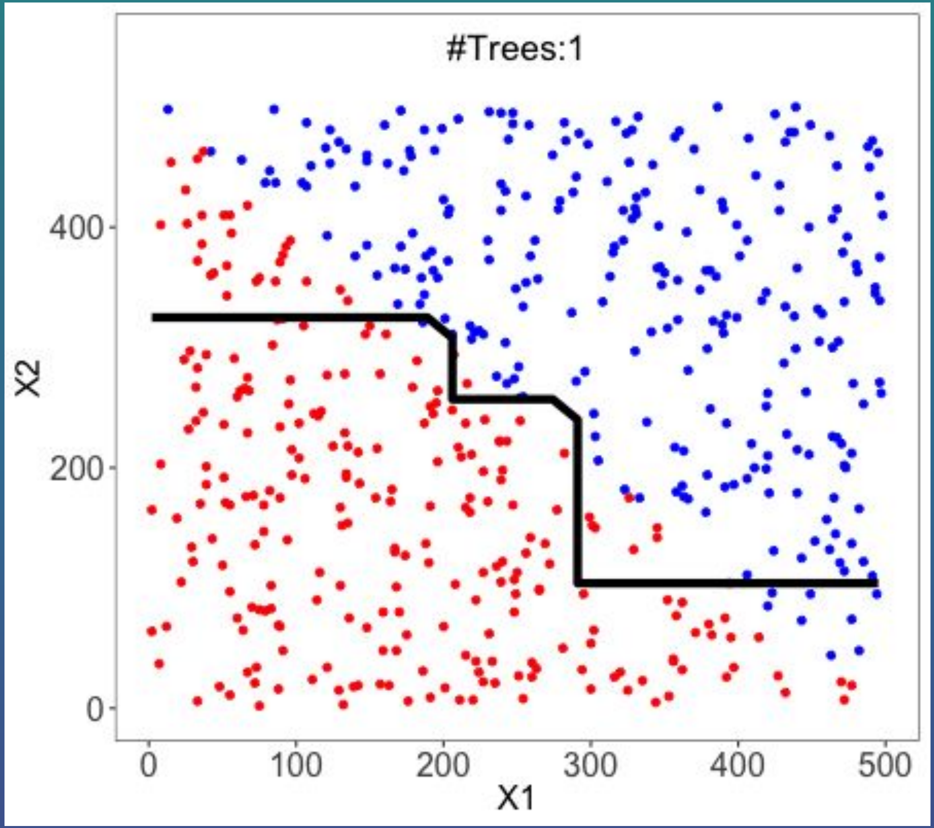
Random Forests



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

Random Forests

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



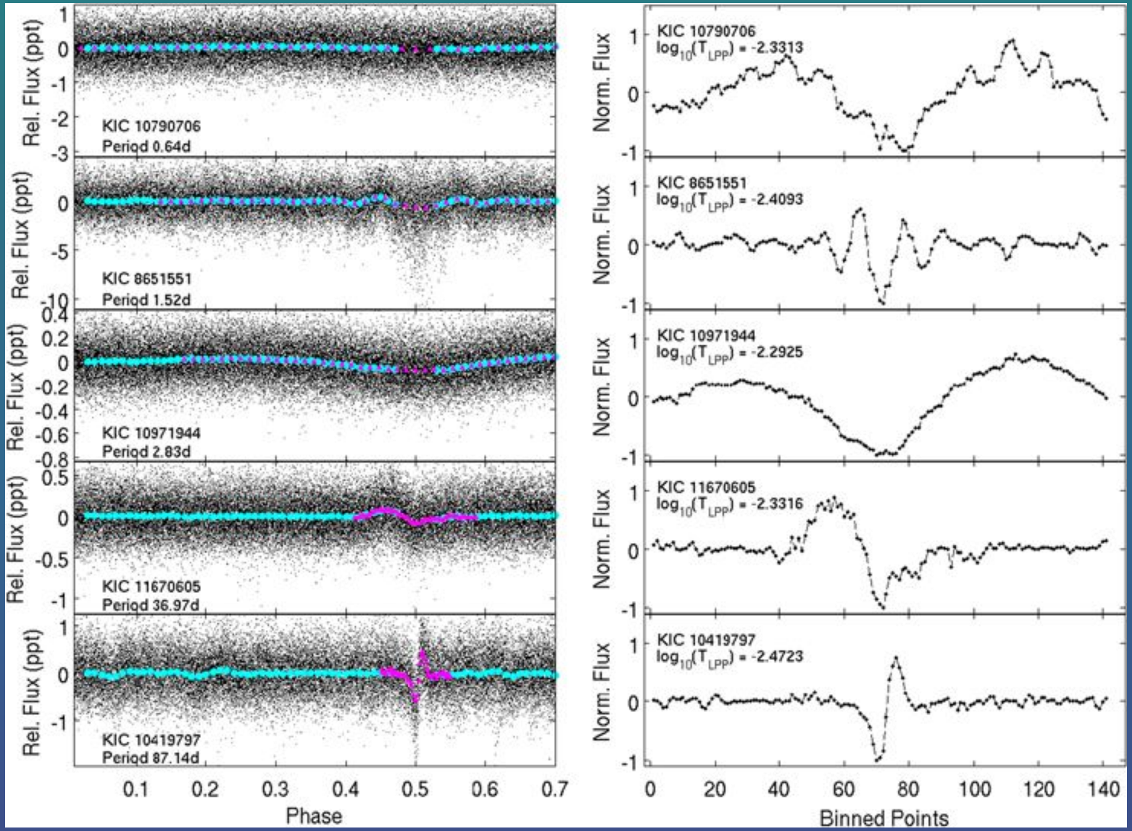
Exoplanet Classification with KNNs

Thompson et al (2015).

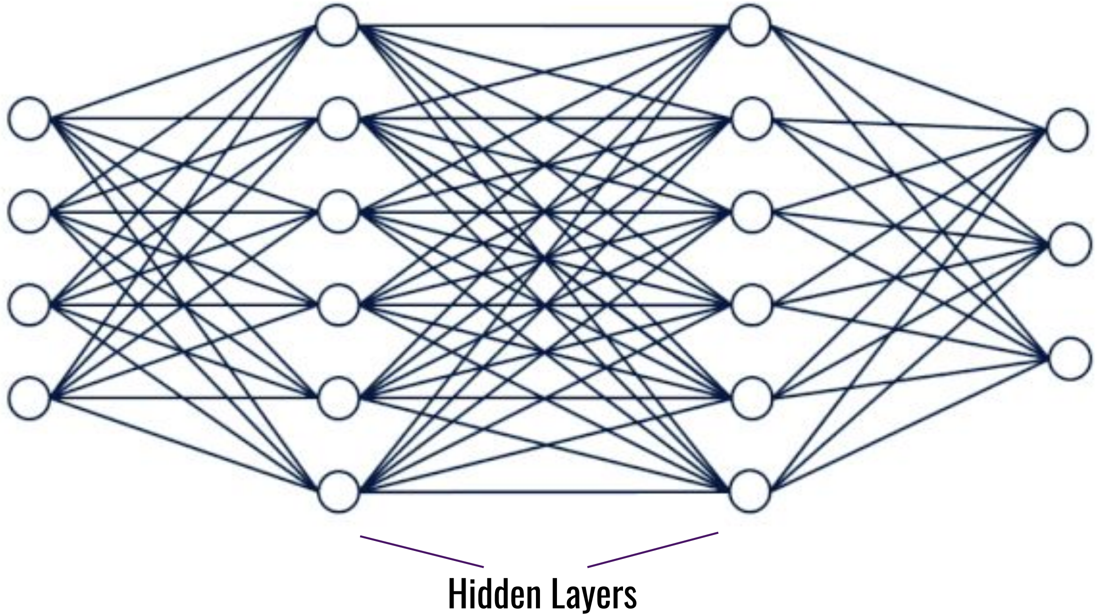
Used a "K-Nearest Neighbours" (KNN) unsupervised approach.

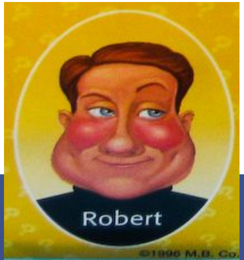
Takes average of nearest labelled features.

Used as inputs binned & normalised phase-folded transits.



Neural Networks

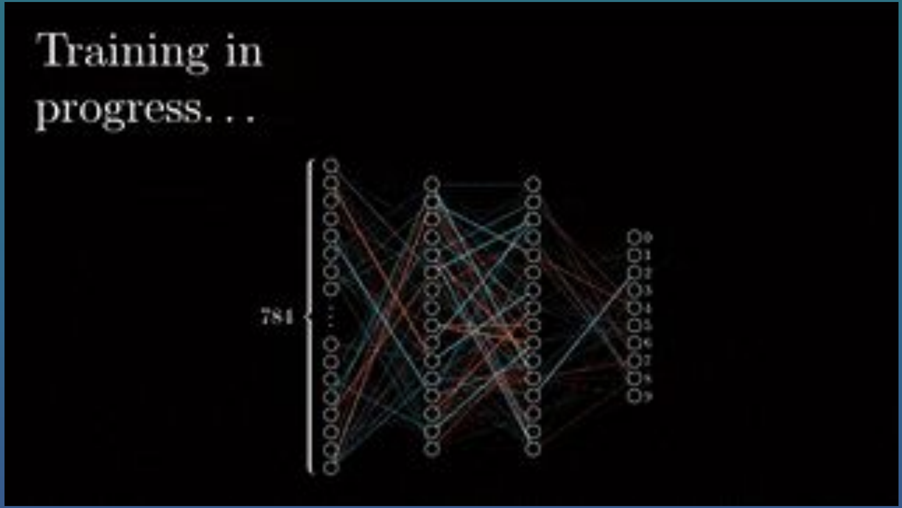




Neural Networks

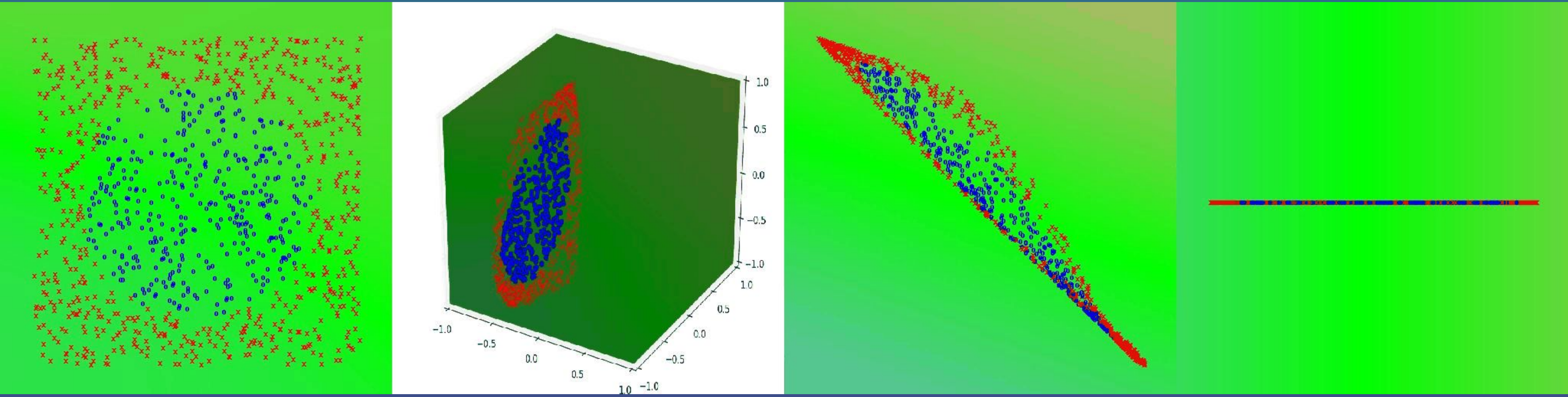
Training neural networks

- 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



Neural Networks

- 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)



Unsupervised Learning (SOMs)

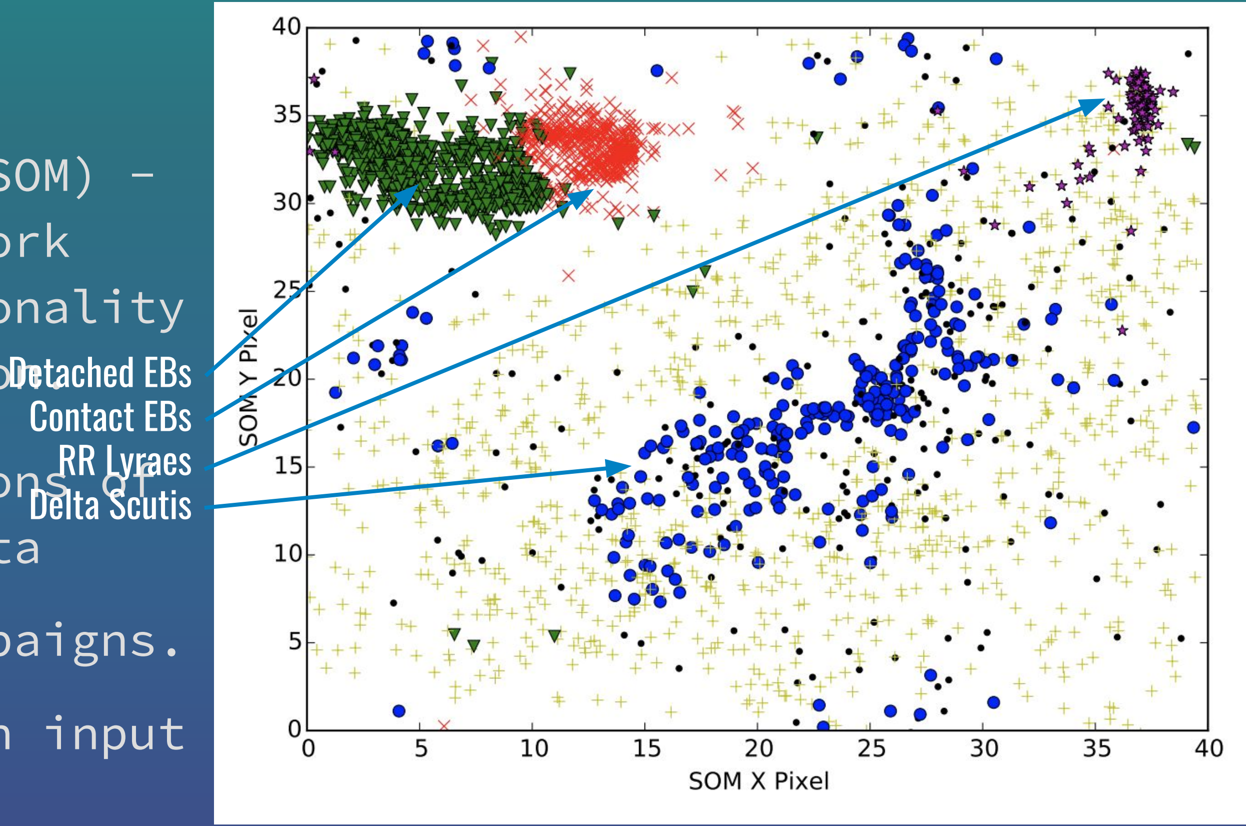
Armstrong et al, 2016

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.

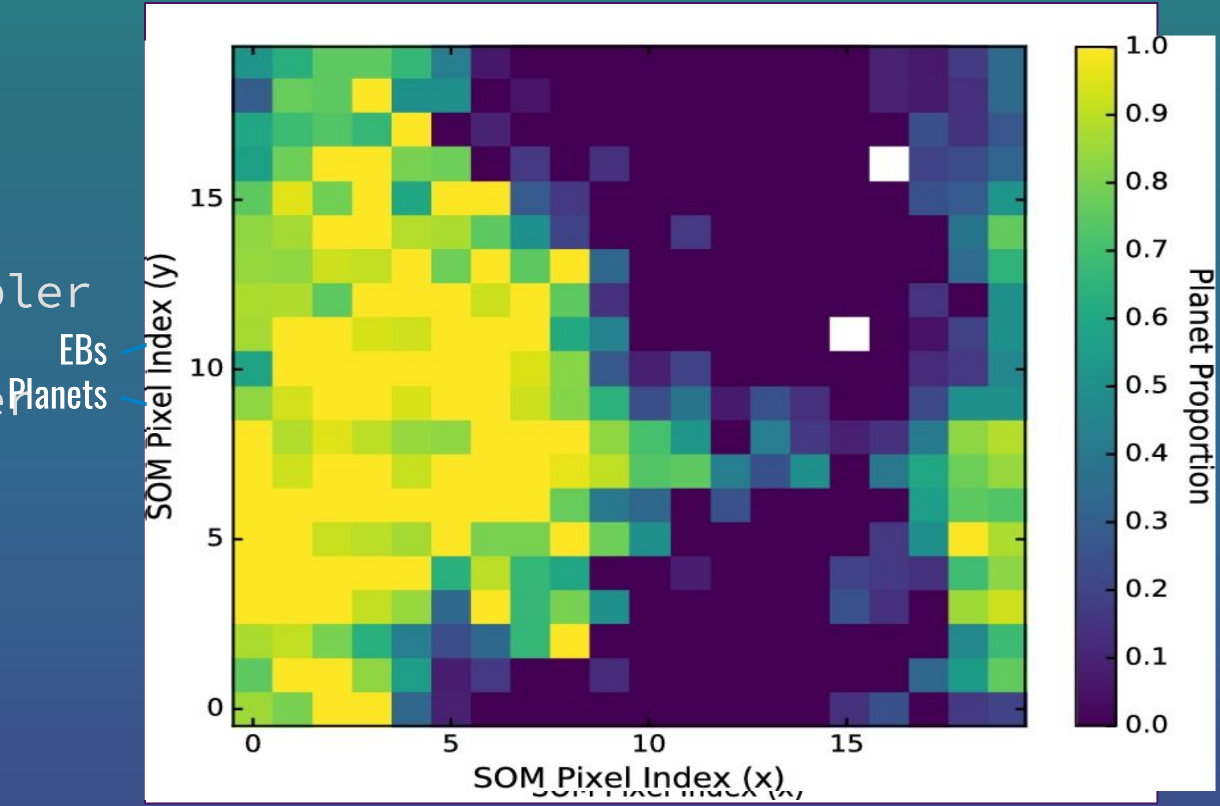


Self Organising Maps for Exoplanets

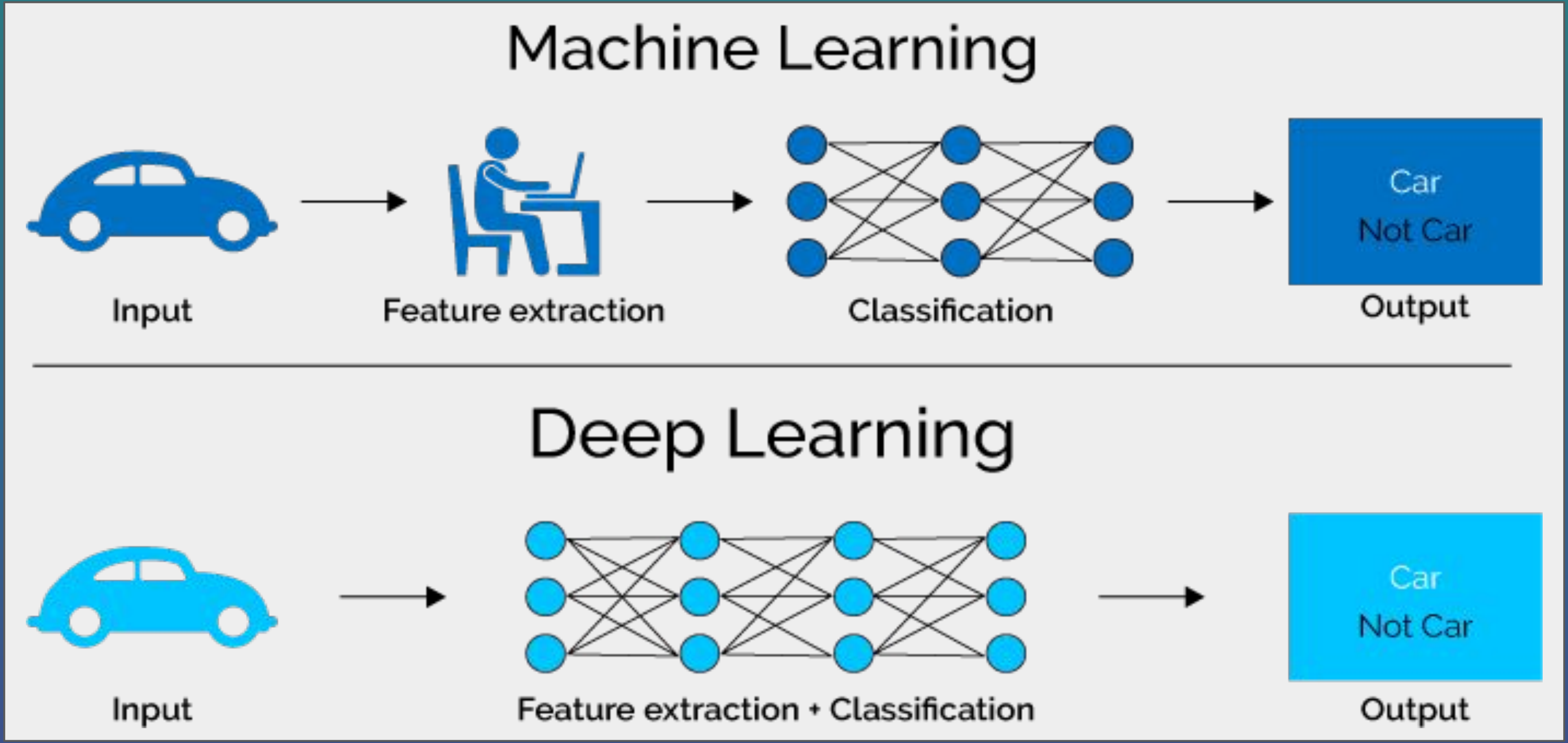
Armstrong et al (2017)

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

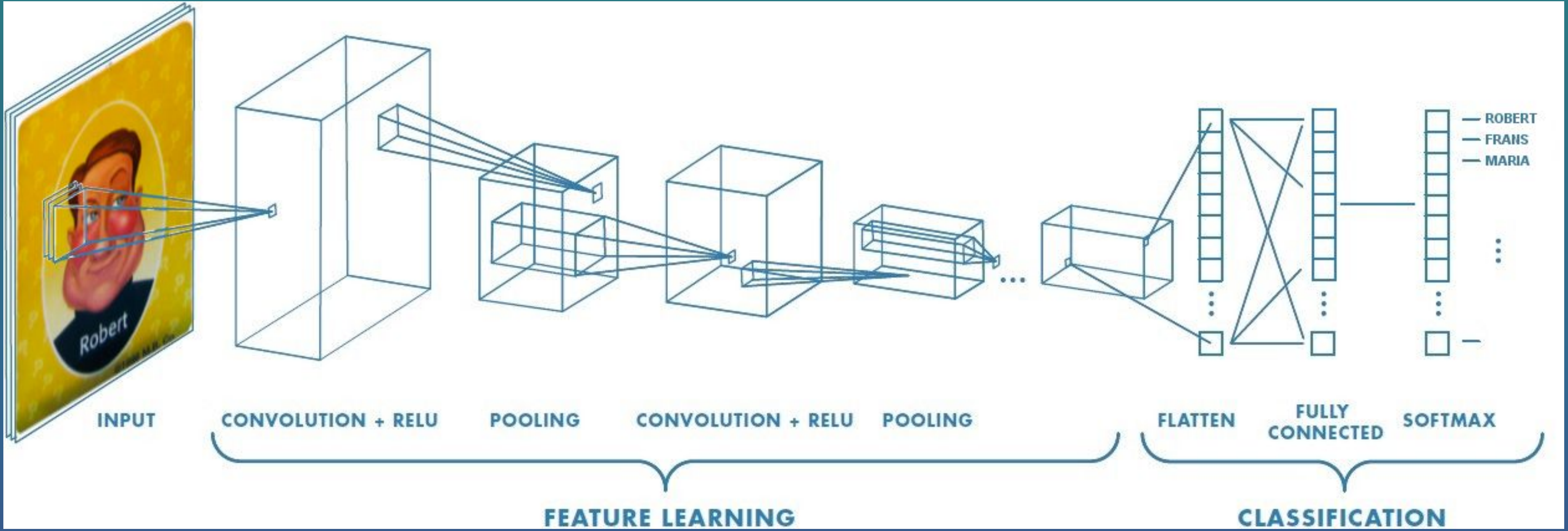
~79% accuracy on Kepler planets



Convolutional Neural Networks



Convolutional Neural Networks

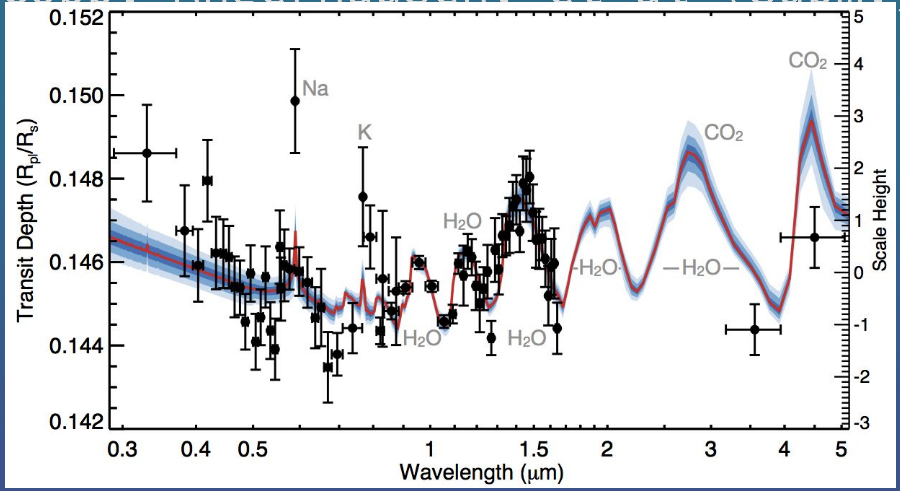


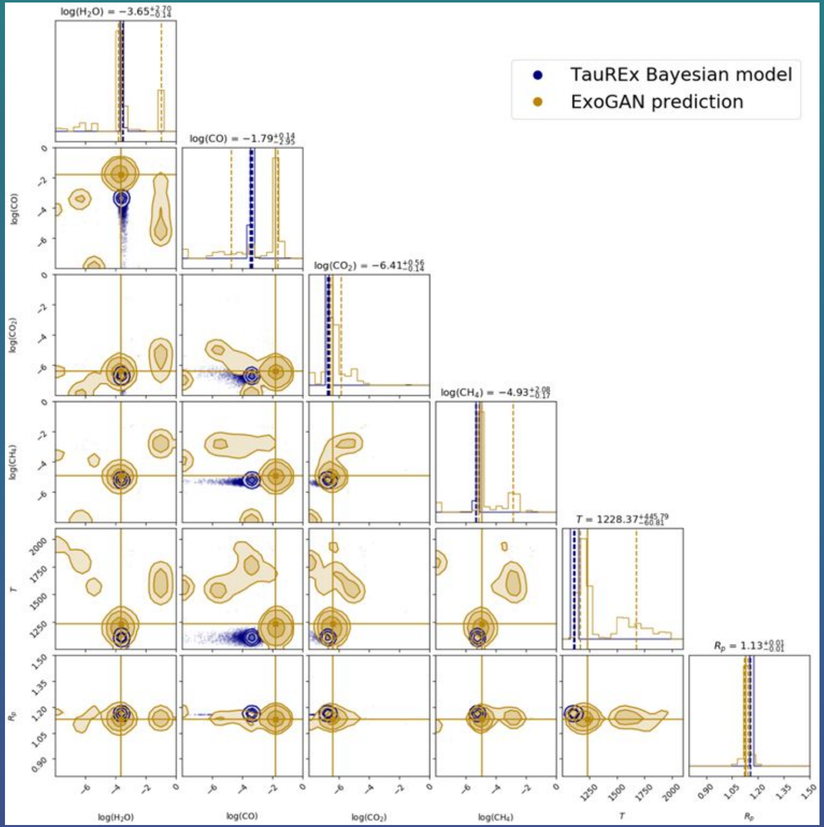
- Raw image “convolved” with range of filters (which themselves are trained with back propagation)
- Enables Feature extraction from the raw data (although raw

CNNs for Atmospheric Retrieval

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

Cobb, Angerhausen, et al (subm.)



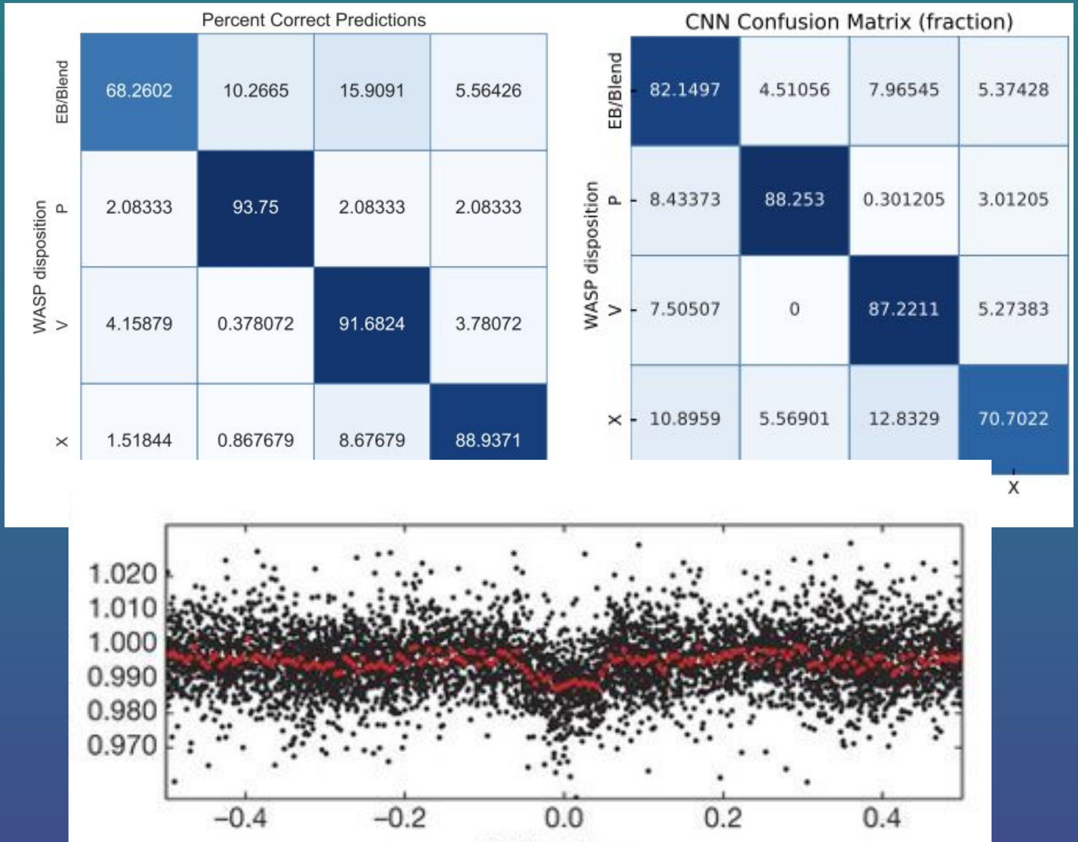


Ground-based transits with RF & CNNs

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

CNNs for Exoplanet Detection

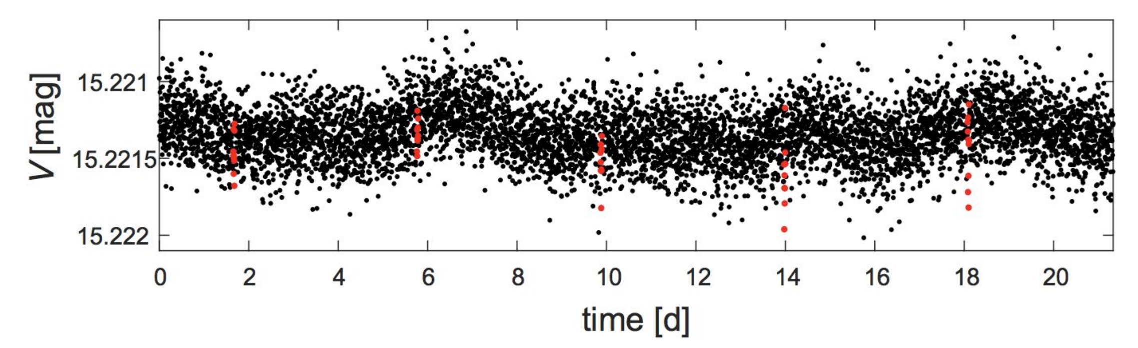
Two parallel papers using neural networks to detect exoplanets:

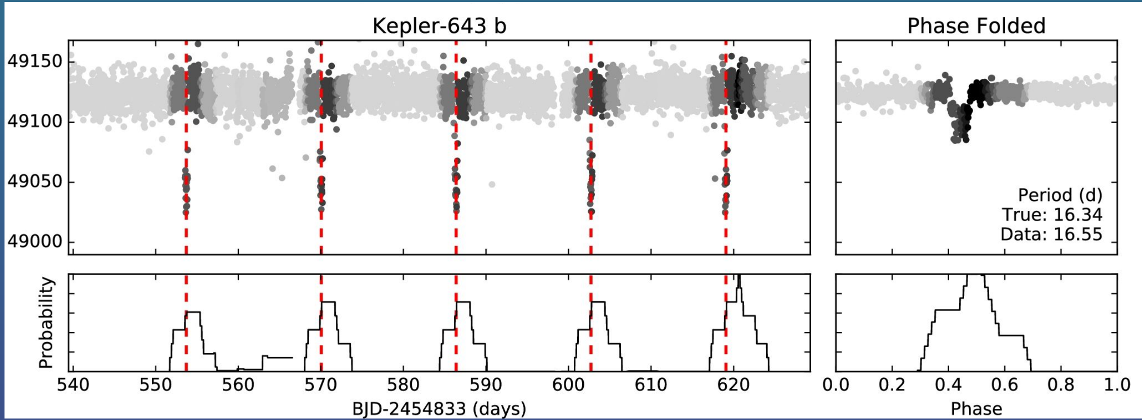
Zucker et al, (2017)

Pearson et al, (2017)

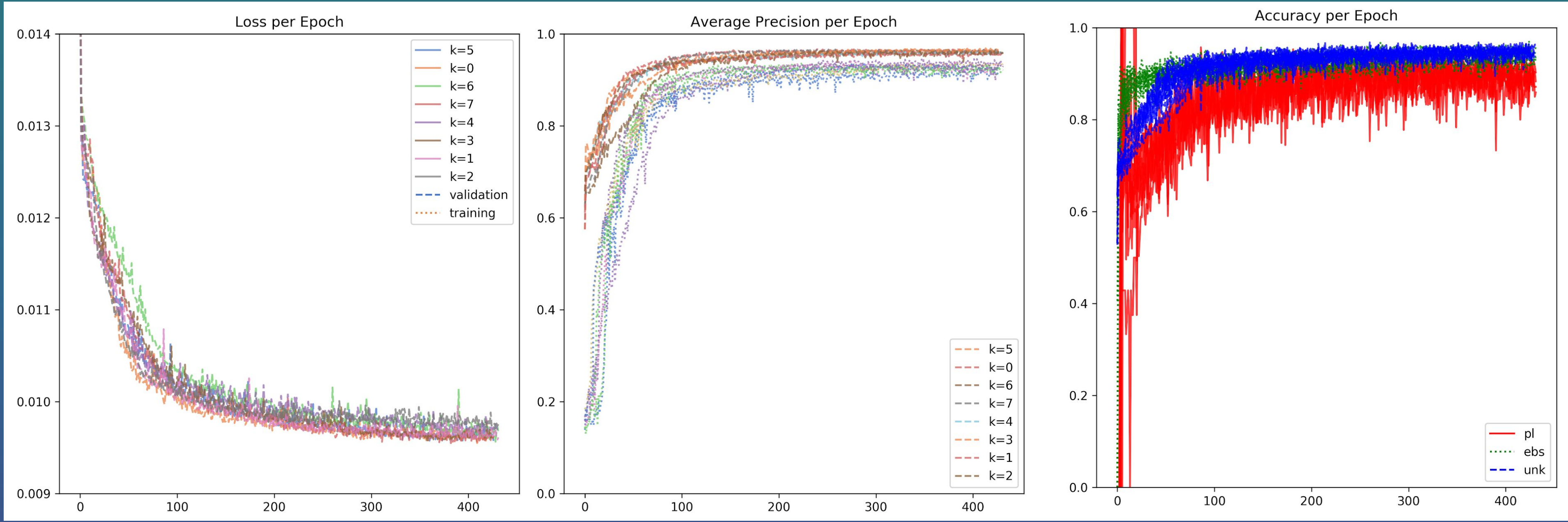
Difficult as neural networks cannot natively learn “periodicity”.

Neither deal with classifying real planets vs false positives





Classifying TESS Simulations



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