RAPID CLASSIFICATION OF TESS PLANET CANDIDATES WITH CONVOLUTIONAL NEURAL NETWORKS

Hugh P. Osborn[1], M. Ansdell[2], Y. Ioannou[3], M. Sasdelli[4], D. Angerhausen[5], C. Raissi[6], J.C. Smith[7], D. Cauldwell[7], J. Jenkins[7]

[1] LAM, France; [2] UCB, CA, USA; [3] Cambridge, UK; [4] Adelaide, Aus; [5] Bern, CH; [6] INRIA, France; [7] NASA Ames, CA, USA

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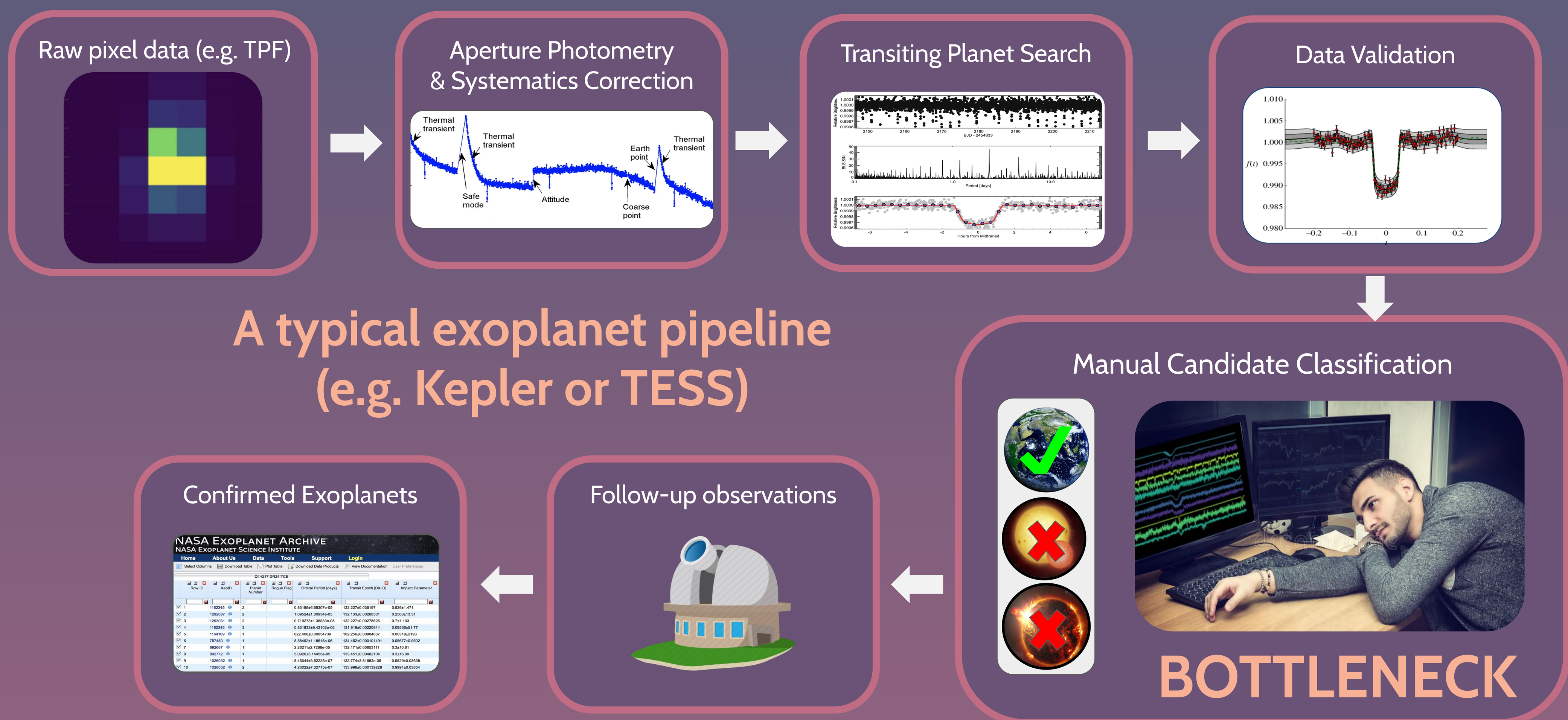
THE PROBLEM



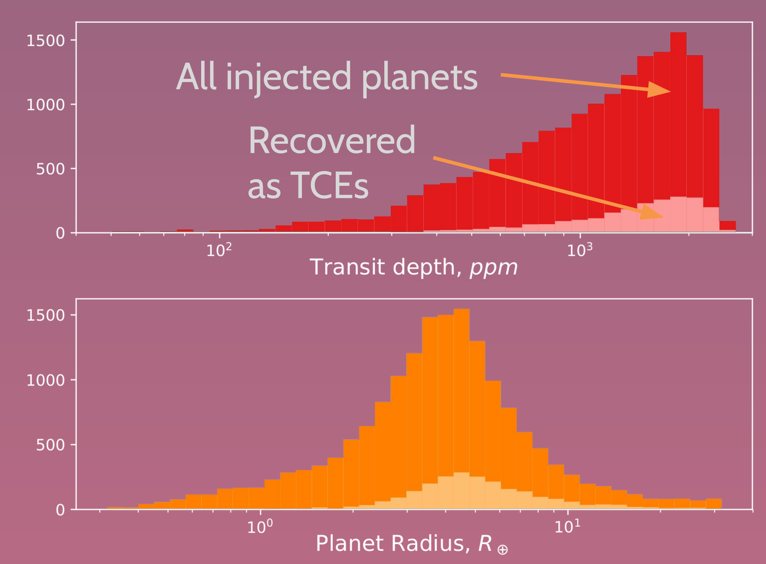
Human candidate vetting is **slow** & **biased** - could it be replaced with Deep Learning?

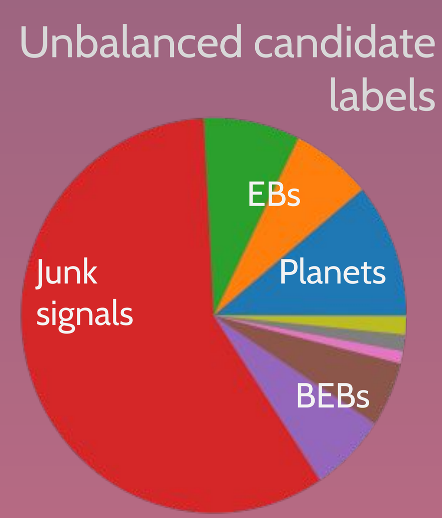
SIMULATED TESS DATA

TSOP-301 - Four TESS sectors simulated with "Lilith" i.e. pixel-level injections of variability, instrumental noise & astrophysical signals.

Injections include: **Planets** (PL), eclipsing binaries (**EBs**), background EBs (**BEBs**).

The **TESS SPOC pipeline** then detected 16 000 candidates (e.g. TCEs) - our train/test samples





RESULTS

Achieves **accuracy** on planet candidates as high as **91.8%** and **average precision** (A.P.) of **95.6%.**

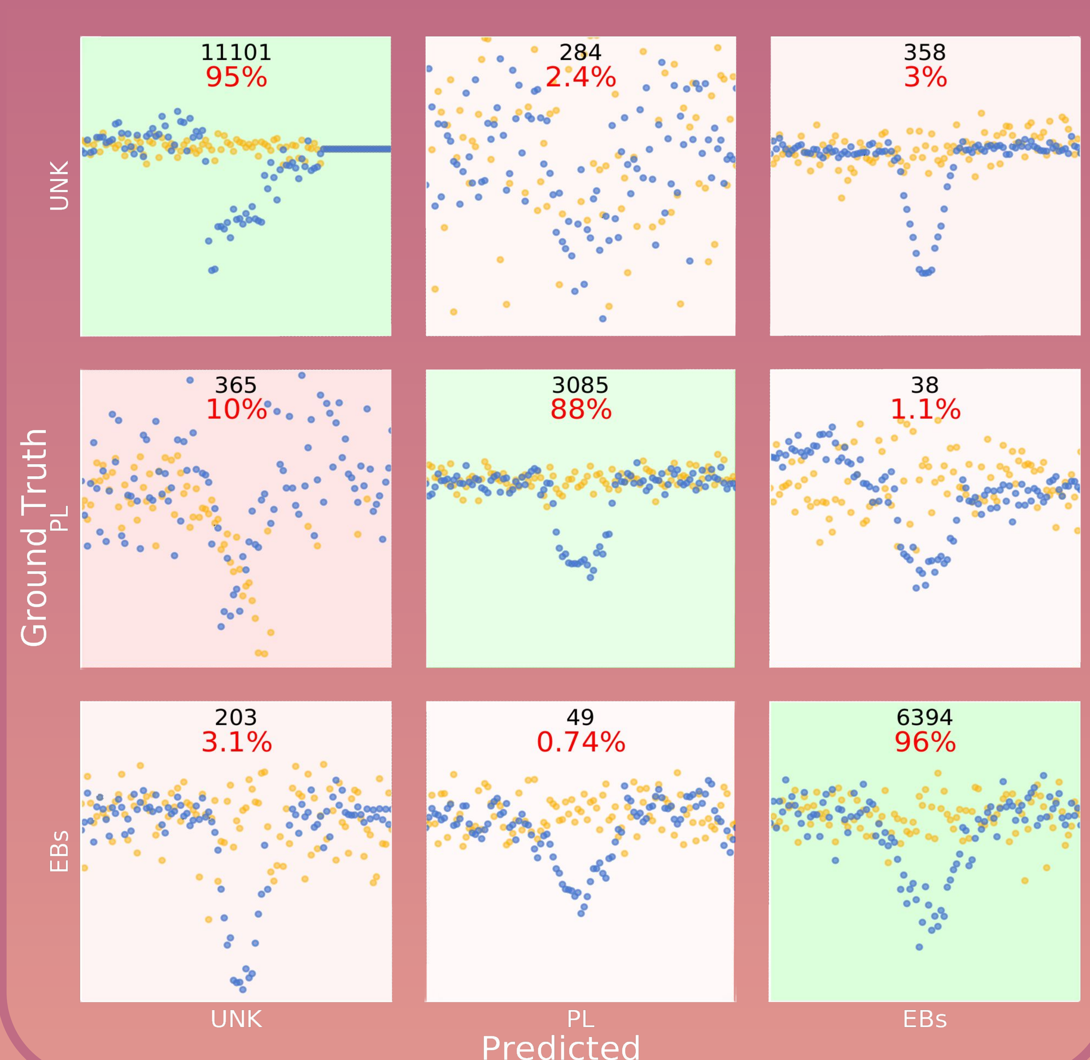
Inspection of 300 predicted planets with "unknown" label reveals >200 are caused by planets (eg monotransits). Including these **boosts planet accuracy to 95.1%**.

Less successful than Ansdell (2019; A.P. = 98.5% in Kepler). Partly due to lower SNR, less centroid quality, & min period in TESS set at 2.

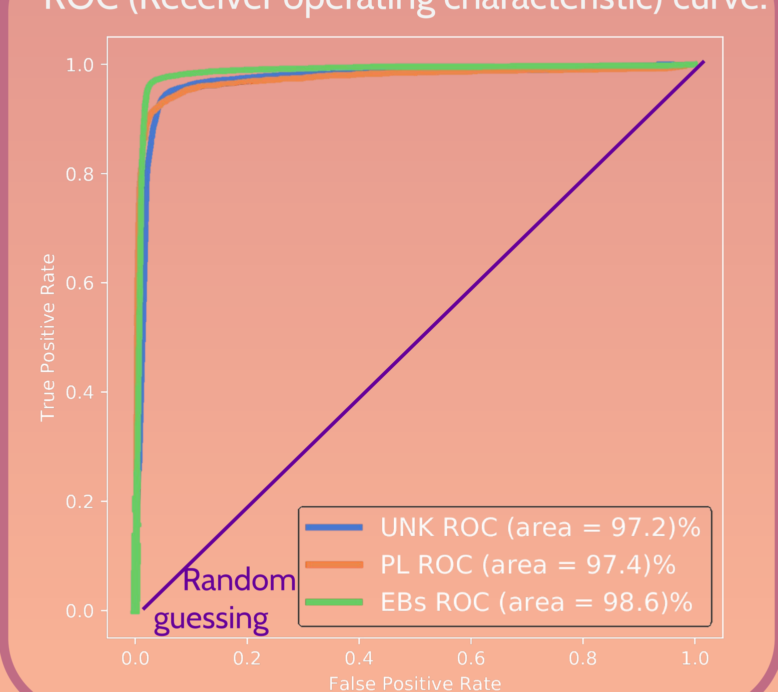
3-class model performs better than binary & 4-class model.

		Accuracy	Recall	A.P.
Binary	Planets	91.8	87.8	95.2
	Unknown	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

Confusion matrix for the 3-class model:

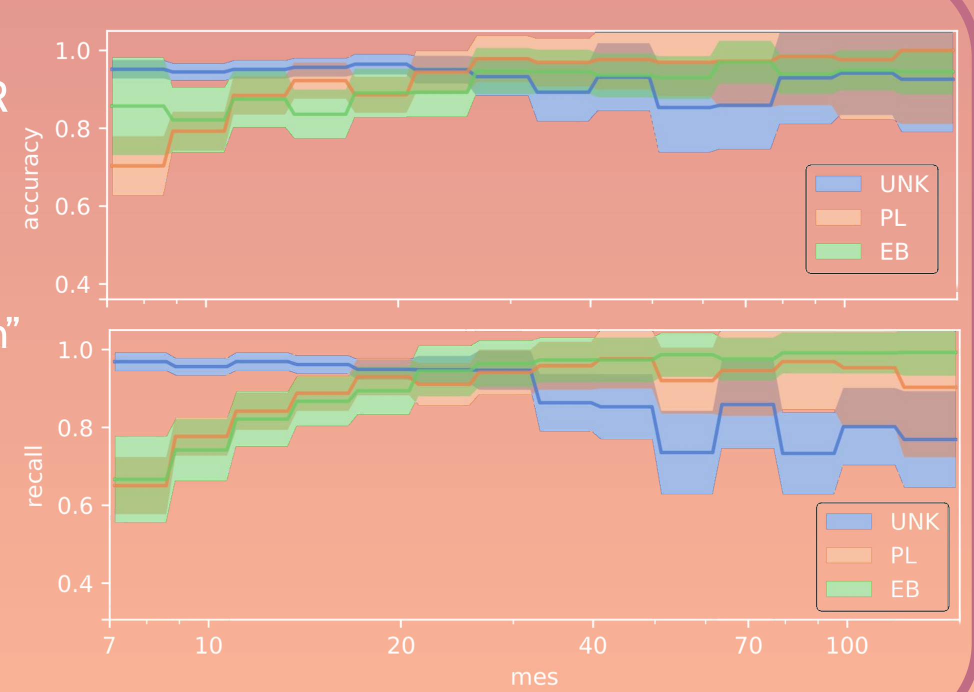


ROC (Receiver operating characteristic) curve:



Recall drops off, as expected, for low-SNR planets & EBs, but still remains ~65% at <9σ.

Surprisingly this is not the case for "Unknown" (e.g. instrumental effects), suggesting ourmodel has learned to identify noise signatures.



THE MODEL

Uses **phase-folded lightcurves** and centroid curves, plus stellar & transit information.

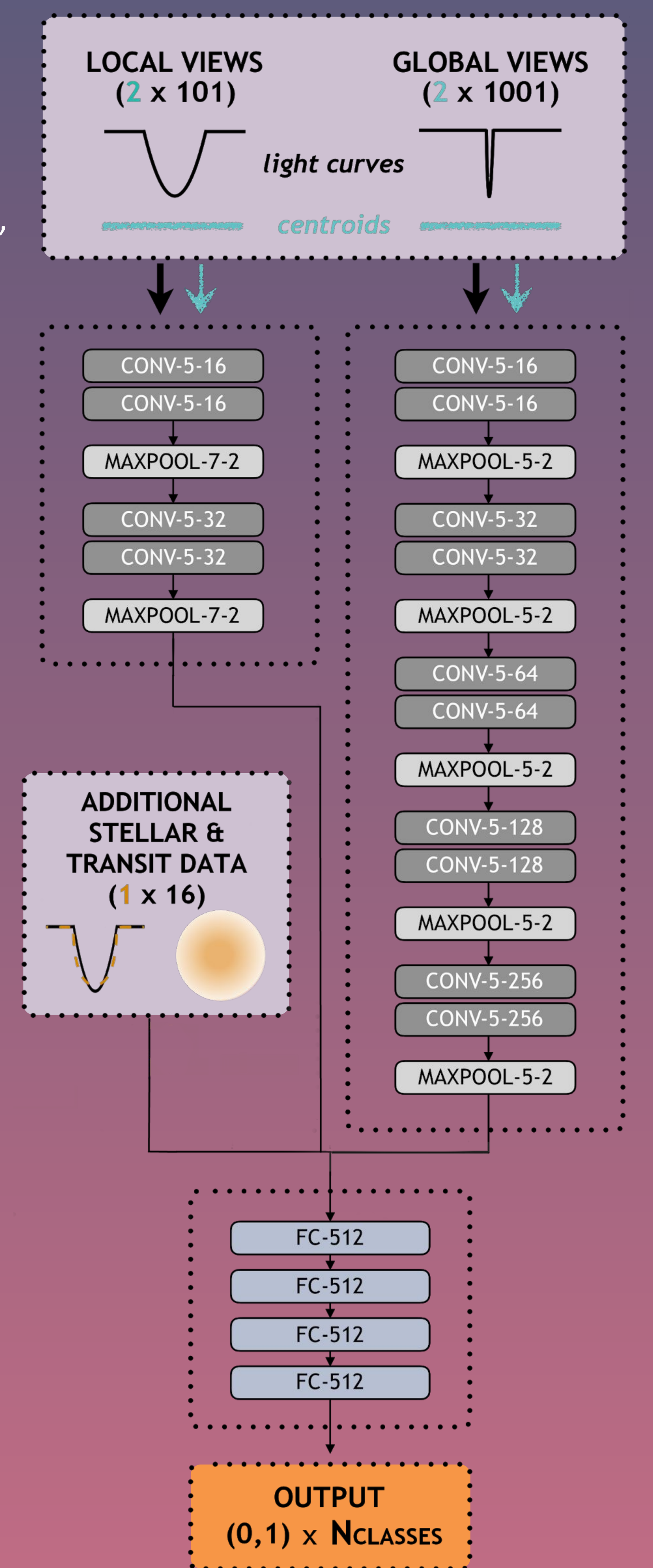
CNN applied to"local view" (window around transit) and "global view" (whole phase).

Adapted from Shallue & Vanderburg (2018) / Ansdell et al (2018).

Reduced number of bins by factor of 2 to increase SNR & speed.

Multi-class labels

Built with PyTorch



OTHER TECHNIQUES USED

Data Augmentation
Slightly modify individual input samples to mimic new data

Balanced Batch Sampling
Each minibatch contains even number of each class

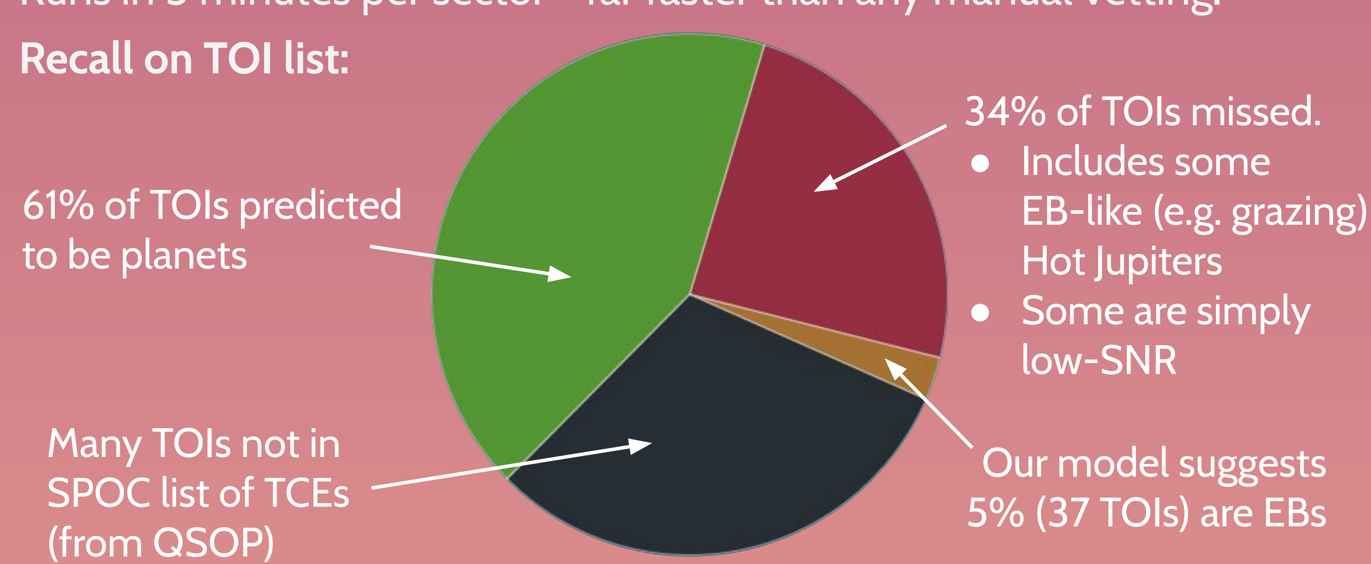
Cross Validation
Split data into k chunks & use each as validation set once

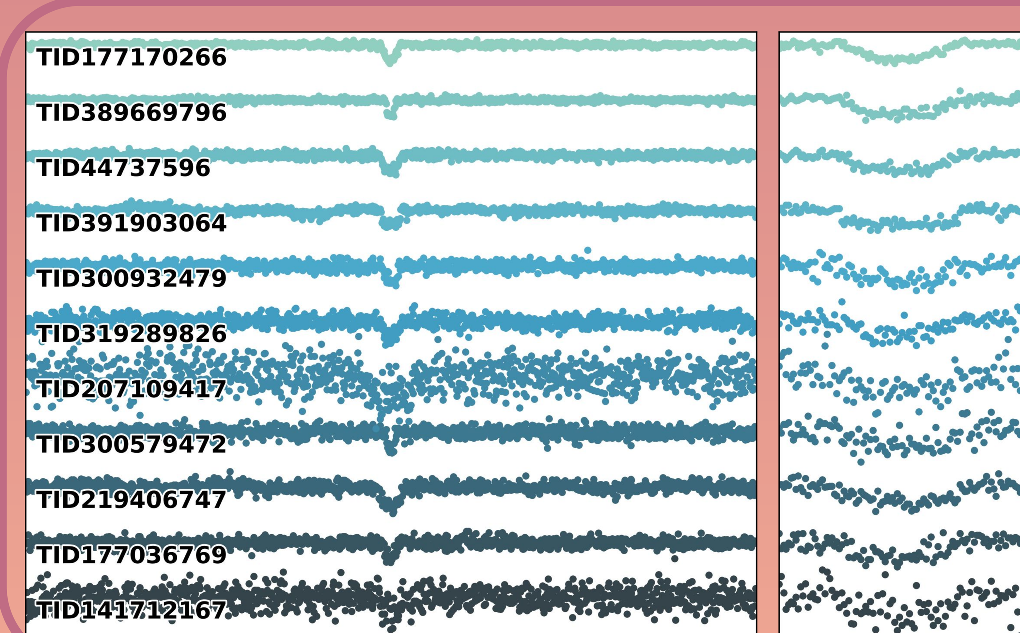
Ensembling
Average many trained models

APPLYING TO REAL TESS DATA

Directly applied the trained model to all TCEs from TESS (sectors 1 to 11). Runs in 5 minutes per sector - far faster than any manual vetting.

Recall on TOI list:





Our model predicts many previously unidentified planet signals. Manual vetting suggests many are binaries, but some appear good candidates.

FUTURE

- Train model on real TESS data - both with real planets & injections into real data.
- Include period-epoch collision metric.
- Apply to MIT Quick-look Pipeline candidates
- Follow-up predicted new planets

REFERENCE: Rapid Classification of TESS Planet Candidates with Convolutional Neural Networks (2019) , Osborn et al, A&A

@exohugh

NASA FDL FRONTIER DEVELOPMENT LAB

LAM LABORATOIRE D'ASTROPHYSIQUE DE MARSEILLE

hugh.osborn@lam.fr