Classifying Exoplanet Candidates with Convolutional Neural Networks: Application to the Next Generation Transit Survey

Artificial Intelligence in Astronomy 2019

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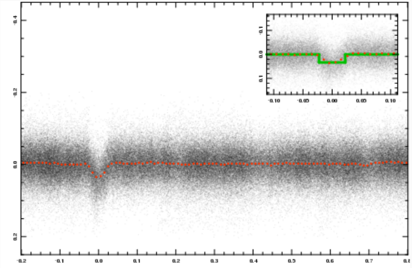
Next Generation Transit Survey (NGTS)



- Twelve independently mounted 200mm telescopes, each with an 8 square degree field of view
- 12 second cadence, with 10 second exposure time
- About 200,000 observations per target depending on field
- Source driven photometry in range 8 to 16th mag in I-band
- Pass-band is 520nm to 890nm, red-sensitive deep depleted CCD.
- See Wheatley+18 for more details...

Transiting exoplanet detection pipeline

Light curve detrending

- Common mode behaviour *(SysRem: Tamuz+05; TFA: Kovács+05)*
- Light curve specific *(Vanderburg+14; TSARDI: Mislis+18; Eigmüller in prep.)*

Candidate detection

- Box-Least Squares (BLS) fitting & derivatives *(Kovács+02, Cabrera+12)*
- Matched Filter *(Jenkins+02, Bordé+07)*

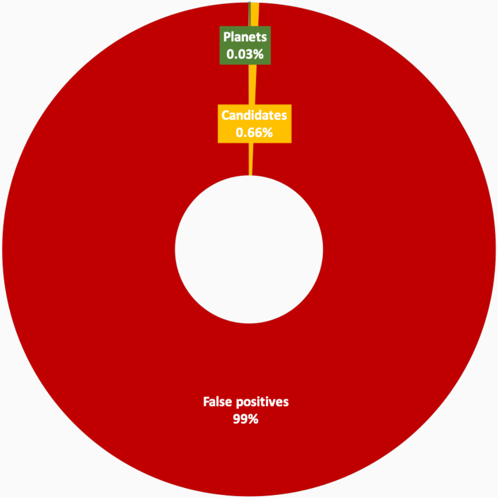
Human vetting

- NGTS: 50k+ candidates; 96% false positives *(Günther+17)*
- Lack of consistency among “eyeballers”

Follow up

- Radial Velocity
- Photometry
- Global modelling

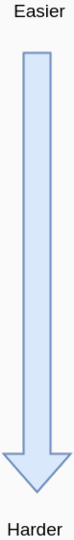
Too many (BLS) false positives...



Candidates:

- 14 planets in dataset
- $\sim$ 350 promising candidates are flagged manually
- over 50,000+ candidates in total

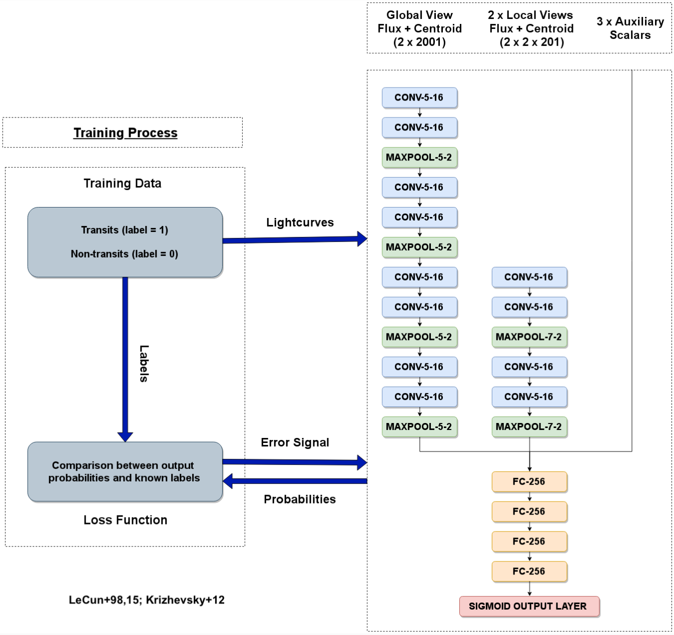
Improving detection efficiency is important for understanding exoplanets



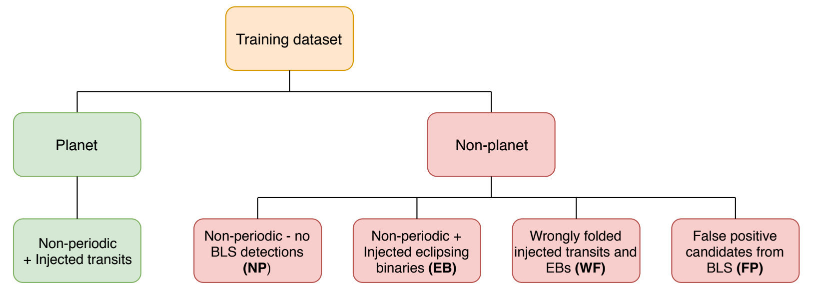
1. Remove obvious false positives detections to speed up manual vetting
2. Improve the recovery of low S/N transits
3. Make better use of limited follow-up time
4. Improve occurrence rate measurements

Method - Classifying NGTS candidates

Convolutional Neural Networks (CNNs) learn their own features

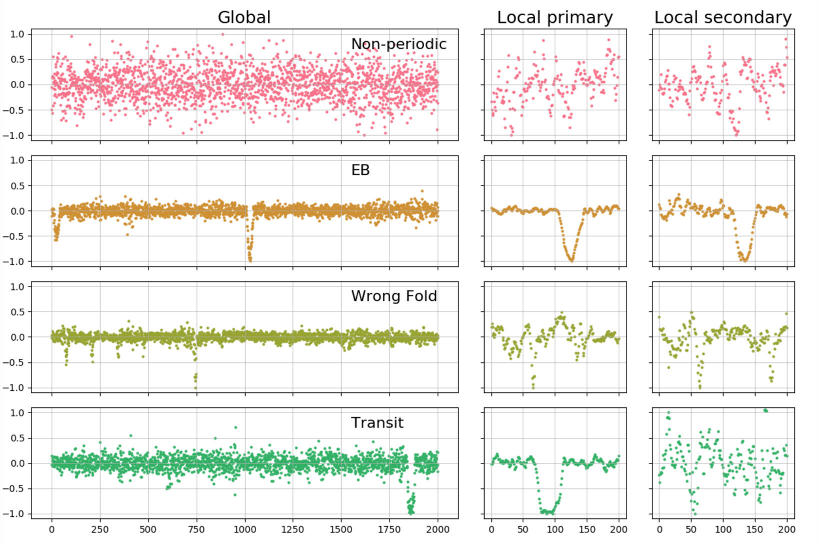


We explore the optimal training dataset composition



- Six different dataset compositions are evaluated
- Each contains 24k training lightcurves in total
- Construct network using PyTorch (Paszke+2017)

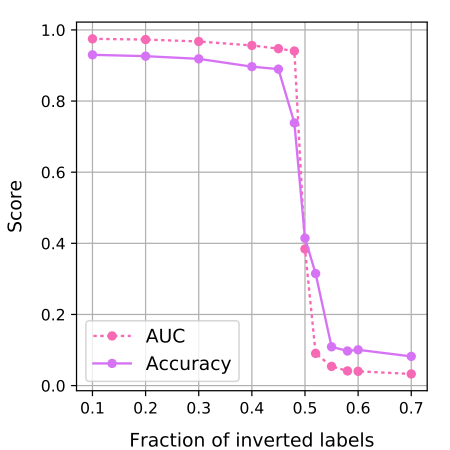
CNN inputs include global and local view



Four example lightcurves - as seen by the neural network.

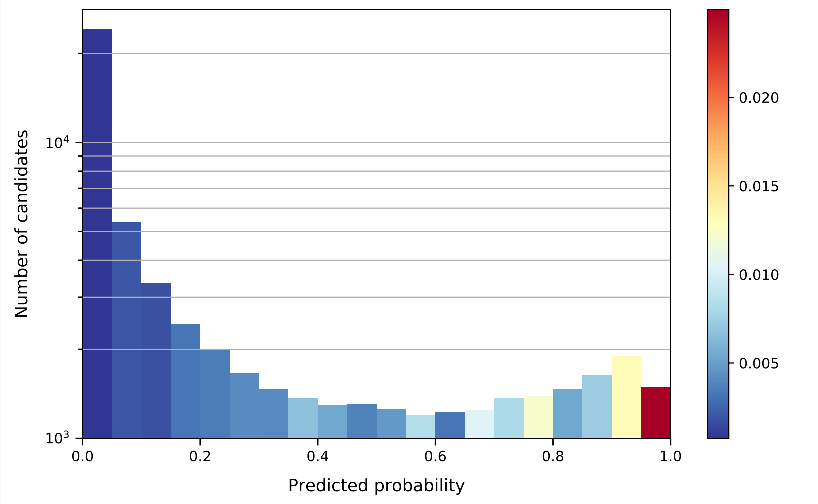
What happens if one of the NP lightcurves has a transit in it?

- Using simulated data with similar noise properties to NGTS
- AUC and Accuracy in the test set as a function of incorrect labels in the training data.
- Related literature: Reis+19 (Probabilistic Random Forests), Rolnick+17 (Massive Label Noise), Li+19 (Gradient Descent is Robust to Label Noise)



Results

The best candidates receive higher planet probabilities

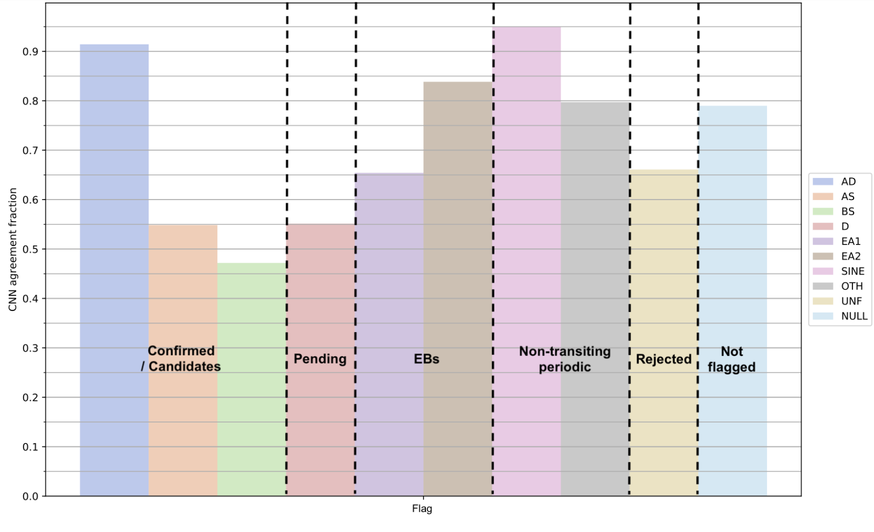


Nearly all confirmed planets with NGTS lightcurves are recovered

Planet name	NP	NP/EB	NP/EB /WF	**NP/EB /WF/VFP**	NP/EB /VFP	VFP
NGTS-1b	0.993	0.996	0.992	0.992	0.991	0.986
NGTS-2b	1.000	0.970	0.970	**0.122**	**0.065**	**0.049**
NGTS-3Ab	0.998	0.995	0.995	0.933	0.927	0.835
NGTS-4b	0.981	0.981	0.981	0.771	0.709	**0.391**
NGTS-5b	0.997	0.996	0.996	0.988	0.991	0.967
NGTS-6b	0.949	0.915	0.915	0.923	0.921	0.969
NOI-101123 (in prep)	0.992	0.983	0.983	0.792	0.729	0.761
NOI-101155 (in prep)	0.996	0.993	0.993	0.860	0.845	**0.146**
NOI-102329 (in prep)	0.995	0.991	0.991	0.741	0.631	**0.441**
NOI-101635 (in prep)	0.998	0.996	0.993	0.945	0.943	0.603
WASP-68b	1.000	0.999	0.999	0.676	0.524	**0.042**
WASP-98b	0.992	0.992	0.992	0.935	0.888	0.94
WASP-131b	0.972	0.783	0.783	0.782	0.780	0.864
HATS-43b	0.999	0.998	0.994	0.786	0.685	**0.273**

VFP = Vetting False Positive, NP = Non-periodic,
EB = Eclipsing Binary, WF = Wrongly folded

CNN predictions show good agreement with eyeballing labels



We determine the NP/EB/WF/VFP model to be the best overall

Model	AUC	Accuracy	Precision	Recall
Eyeballing flags:				
VFP	77.9 ± 0.4	87.7 ± 0.9	1.37 ± 0.04	42.0 ± 2.0
NP/EB/VFP	77.5 ± 0.5	77.6 ± 0.9	1.6 ± 0.03	60.0 ± 2.0
NP/EB/WF/VFP	76.5 ± 0.4	74.6 ± 1.1	0.98 ± 0.02	63.0 ± 2.0
NP/EB/WF	65.2 ± 0.4	41.7 ± 1.1	0.54 ± 0.01	81.0 ± 2.0
NP/EB	63.9 ± 0.4	38.2 ± 1.1	0.53 ± 0.01	84.0 ± 1.0
NP	50.3 ± 0.6	9.4 ± 0.5	0.39 ± 0.01	91.3 ± 0.9

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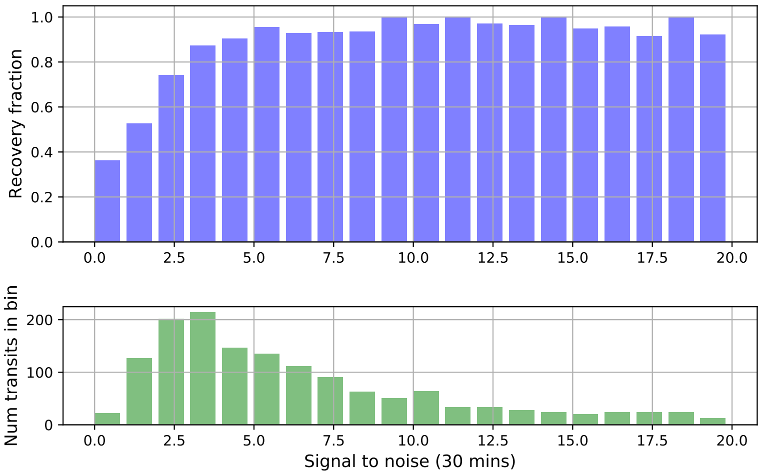
Transit recovery as a functions of signal to noise



Summary

- Using a threshold of 0.1 we can reduce the number of false positives by half, while keeping all planets and 91% of promising candidates.
- CNN predictions show good agreement with eyeballing labels $\sim$ 75% accuracy (threshold of 0.5).
- Many new candidates identified with probability > 0.95 - require further vetting.
- Future work: add network inputs, continue optimising training data composition, improve architecture.

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