Finding Exoplanet Transits with Machine Learning

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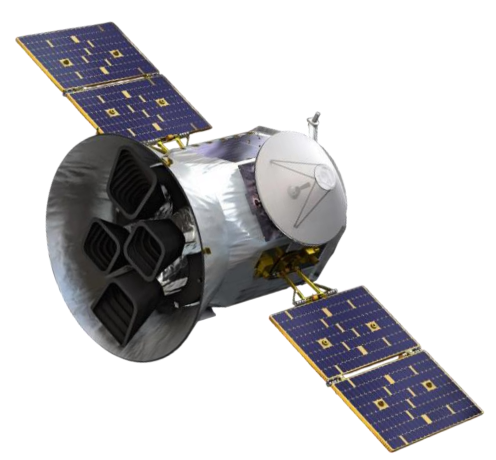
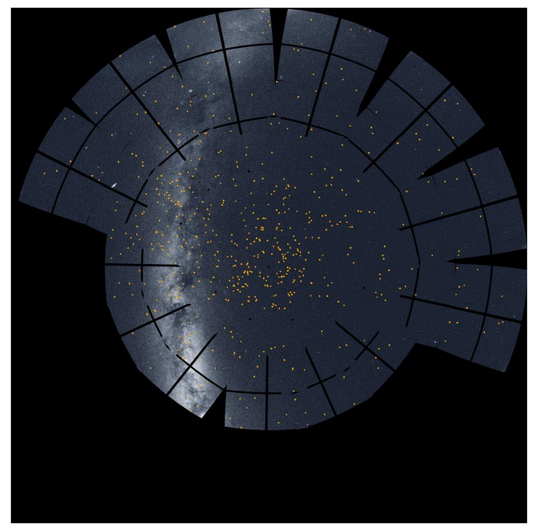
Transiting Exoplanet Survey Satellite

~ TESS surveys a hemisphere every 13 months
~ Scans the sky in chunks called "sectors"
~ Each sector lasts for one month, aligned with the lunar cycle
~ Light curves contains data gaps due to Sun/Moon brightness and data download

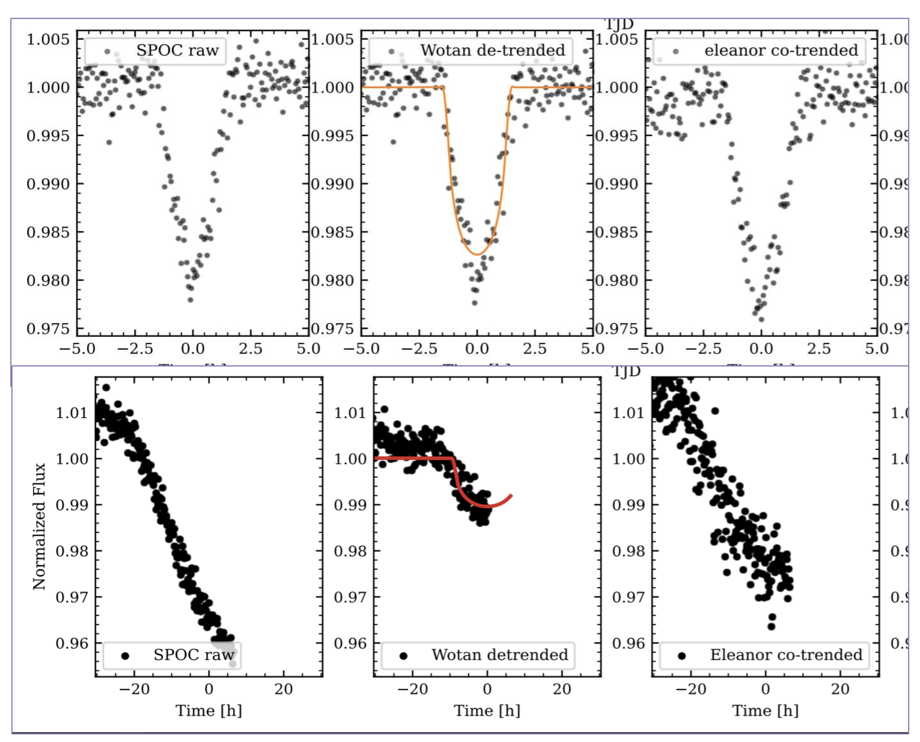




Deep-Transit

~ Machine Learning algorithm that utilized YOLOv3 for object detection
 ~ Originally trained on Kepler space telescope data, which observed continuously (no data gaps)
~ *DT* commonly flags gaps as transits in TESS data
 ~ Nearly 50% of the *DT* flagged objects are gaps!
 ~ Time consuming to spot actual transits out of "junk"

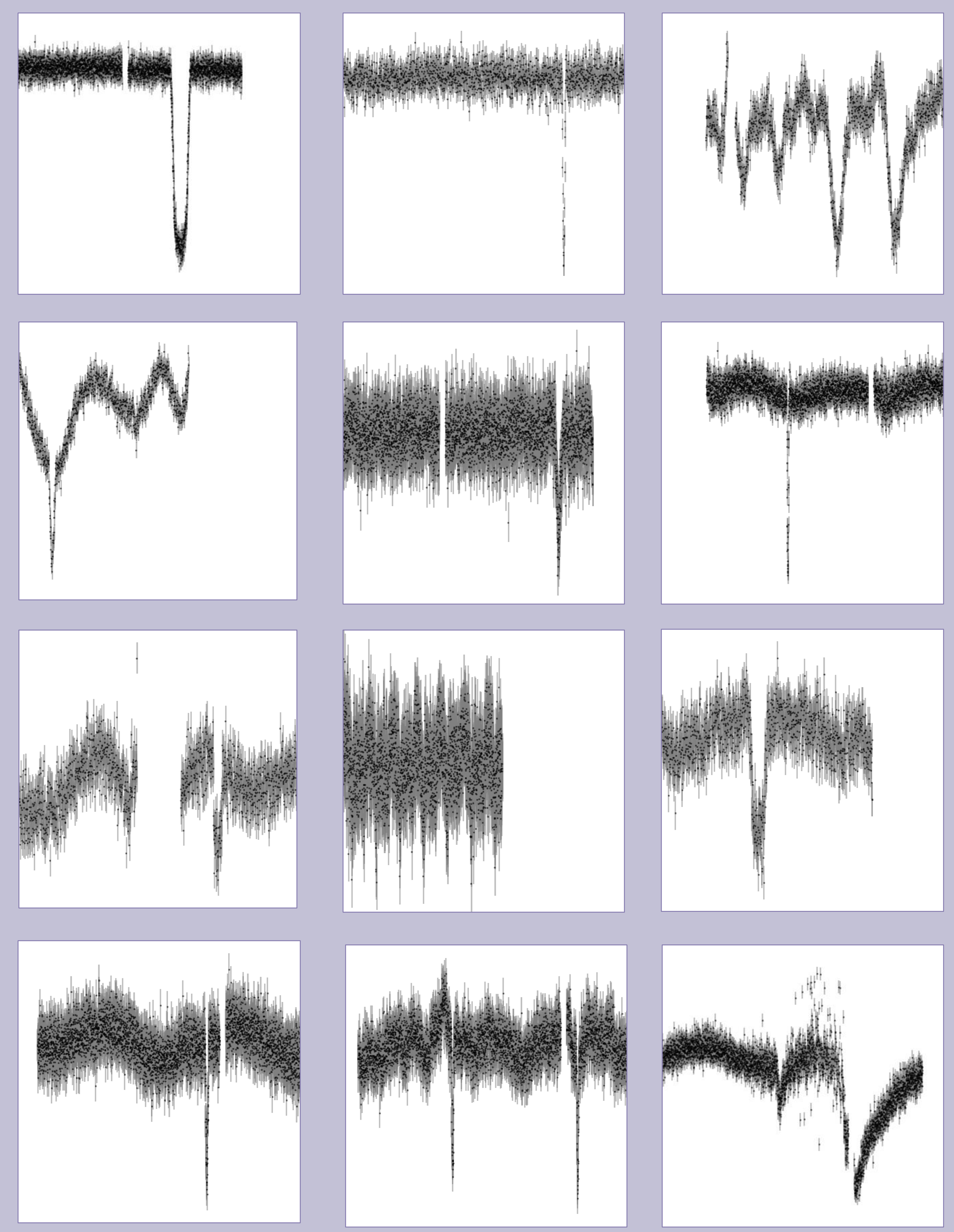
TESS observes ~100,000 light curves → DT flags ~ 1000 targets with "transits" → Citizen scientists manually identify ~ 250 transits → UNM team retains a couple dozen events



DT must be retrained on TESS data!!

Training Process

~ Deep Transit is trained on image files coupled with label files
 ~ Each image is 416 x 416 pixels
 ~ Label file consists of [x and y centers, width, height, signal-noise ratio]
~ Limitations
 ~ TESS images with low signal-noise ratio limits learning capabilities
~ DT model trained on 140,000 Kepler light curves
 ~ We have access to only 39 TESS sectors
~ Choices made to optimize training
 ~ Decreased to 16 sectors, which have been vetted, and extracted 2,691 unique TICs
 ~ Expanded the dataset from 2,691 to 10,756 through multiple image generation and image mirroring transfer learning



↑ Which identified "transits" are junk? ↑

Where We Are

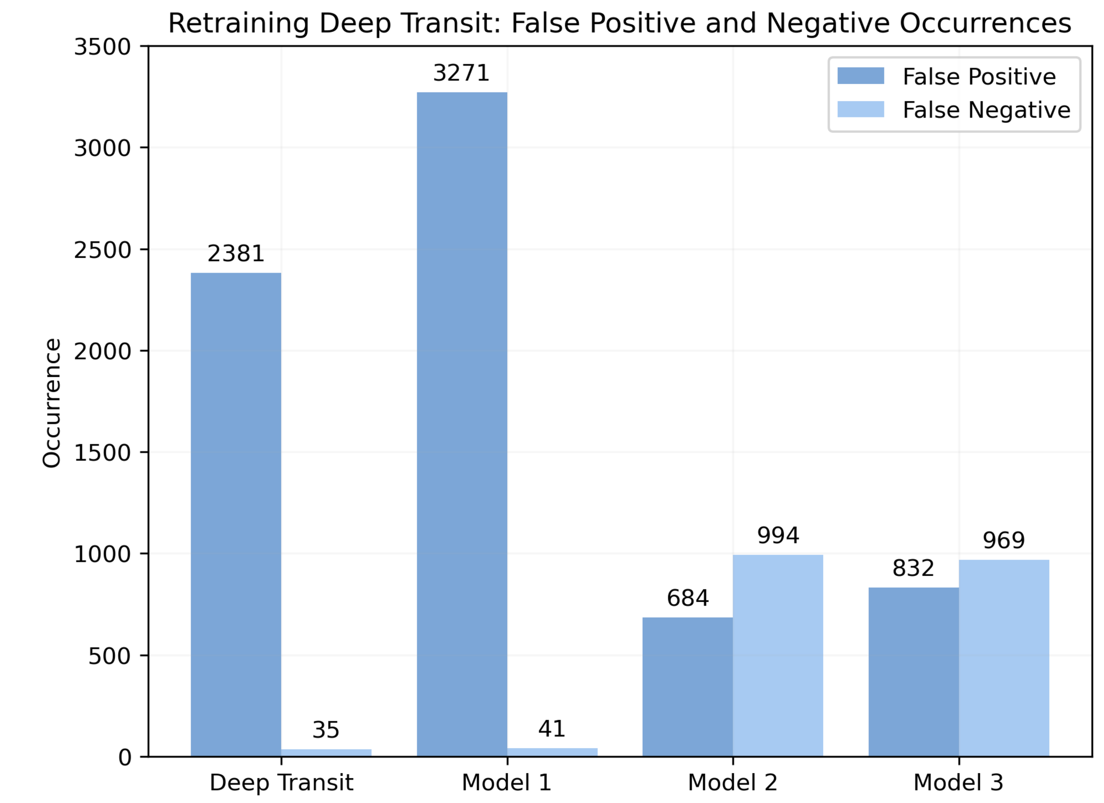
~ In Summer 2025, 10 models were trained
 ~ 15 sectors, 2,730 light curves
 ~ Adjusting batch and epoch sizes
 ~ Had 2 rounds of vetting to refine data

Model	Test Results (Number of Events)			
	0	1-6	7+	Max
DT	223	2374	134	32
1	75	3	2653	6648
2	56	12	2663	925
3	3	0	2728	9144
4	2731	0	0	0
5	2652	17	62	152
6	2352	361	18	25
7	206	10	2515	7110
8	0	0	2731	5137
9	2599	122	10	10
10	2731	0	0	0

~ Analysis led to the conclusion of a small sample size causing model overfitting, so the project continued into Fall 2025 with a new sector
~ To expand the dataset, 4 images were generated from each transit

Model	Precision	Recall
DT	0.607	0.978
1	0.566	0.967
2	0.568	0.976
3	0.570	0.999
4	-	0.000
5	0.650	0.033
6	0.605	0.148
7	0.550	0.893
8	0.570	1.000
9	0.564	0.048
10	-	0.000

~ Two images generated with different x-axis values
~ Both both images had a mirrored pair
~ Ran 3 models in increased training set



~ These models points to a decline in FPs compared to the *DT*, but at the cost of an increased in FNs
~ Running 3-6 more iterations with this larger training set will inform us of the optimal training parameters

Next Steps

~Run more models with current dataset and adjusting parameters
 ~ Keep batch size 32, 64, or 96
 ~ Increase epoch values (50-200)
~ Ways to increase machine learning training set:
 ~ Including newer sectors
 ~ Insert synthetic transits into "quiet" light curves
 ~ Randomized split and swap of transit events
 ~ Increase data set by order of magnitude (~100k)
~ Adjust dataset split for training method
 ~ Current split is 77/14/09 (percentage) for train, validate, and test
 ~ Aim for closer split of 85/10/05 as dataset increases

~ Use Center for Advanced Research Computing (CARC) for new training models, ideally allowing for quicker code running and larger epoch sizes.
 ~ May be able to parallelize code to optimize time, or train multiple unique models simultaneously
 ~ Optimal for personal storage on local devices

References & Acknowledgements

Kaiming Cui et. all, Identify Light-Curve Signals with Deep Learning Based Object Detection Algorithm. I. Transit Detection (2021)

TESS images courtesy of NASA

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Contact Me! →