Developing Algorithms for Detecting Microlensing Signals in TESS

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Any Questions?

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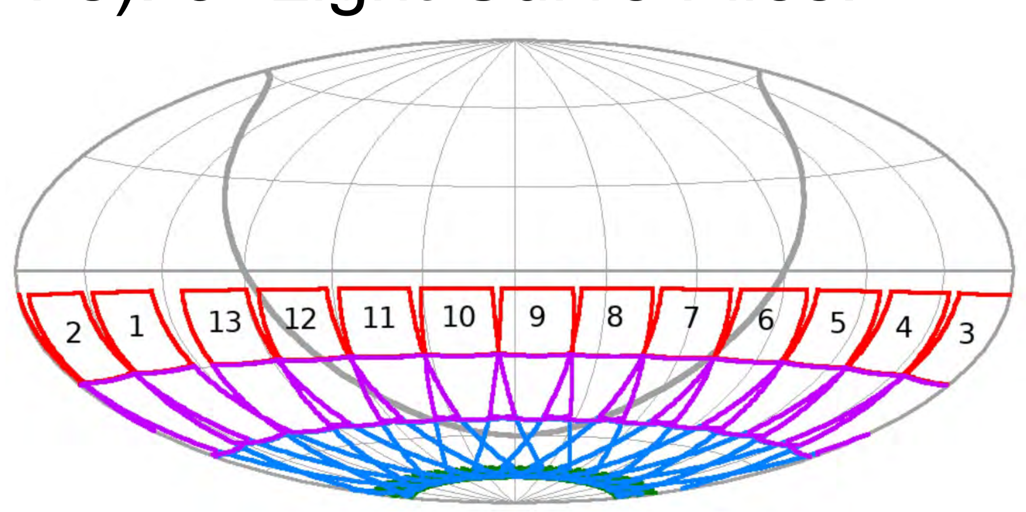
Introduction

Microlensing is a unique method to find dark compact objects in the universe that are otherwise hard to see. The Transiting Exoplanet Survey Satellite (TESS) primarily focuses on finding transiting exoplanets, and we aim at using its comprehensive all-sky survey and high cadence to look for microlensing candidates. **Finding microlensing events in an all-sky, high-cadence survey is indeed very exciting, but it also enables evaluation of the performance of detection methods and tests our predictions from the simulations.**

TESS Light Curves

- Each sector is 24° × 96° and is fully observed in ~27 days.
- 69 sectors in 5 years: 30 min, 10 min and 200 s cadence.
- Pixel scale: 21 arcseconds.
- Sensitive to 600 – 1000nm (from blue to the near-IR).
- **TESS data products:** 1- Full Frame Images (FFIs). 2- Target Pixel Files (TPFs). 3- Light Curve Files.



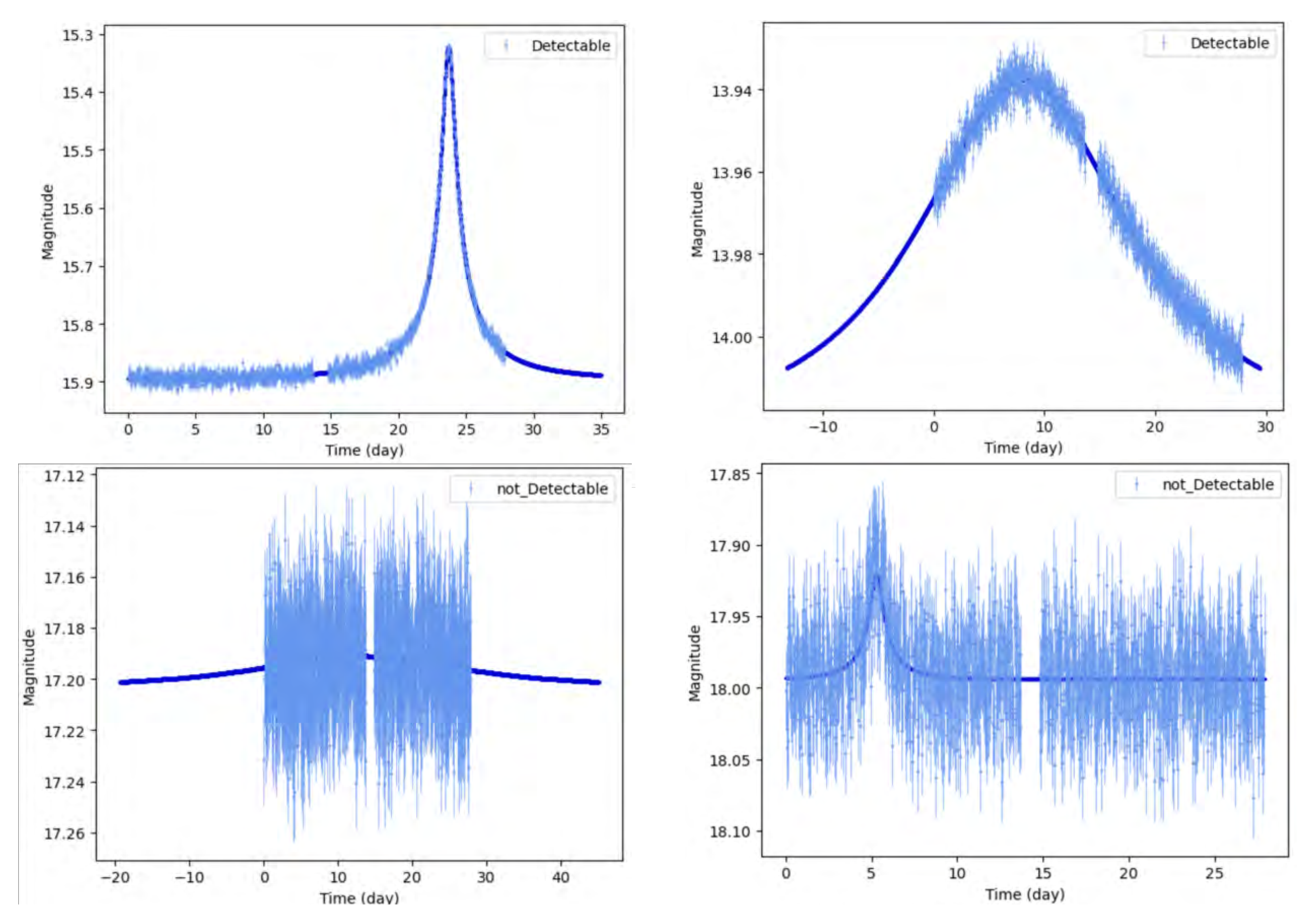
Observations during year 1 comprised Sectors 1-13.

Goals

- Find out what we expect from TESS.
- Use traditional detection methods and a deep learning model to find microlensing events in TESS.

Simulations

- Simulated for sector 12 in the Galactic disk as [1] did for LSST.
- Source brightness in the T-band from Gaia absolute magnitudes [2].
- u_0 and t_0 uniformly in [0,1] and [0,27.89] respectively.
- Accounting for cadence and gaps in sector 12.
- Photometric noise is obtained experimentally from TESS-SPOC.



Detectable and not-Detectable signals after applying detectability criteria.

Methods

1. We implement an algorithm used by the KMTNET team [3] and look for candidates.
2. We use transformers, a type of deep learning model primarily used on language data, trained on TESS and the simulations.

Two-parameter PSPL Fit

We implemented the KMTNET detection algorithm as described in [3].

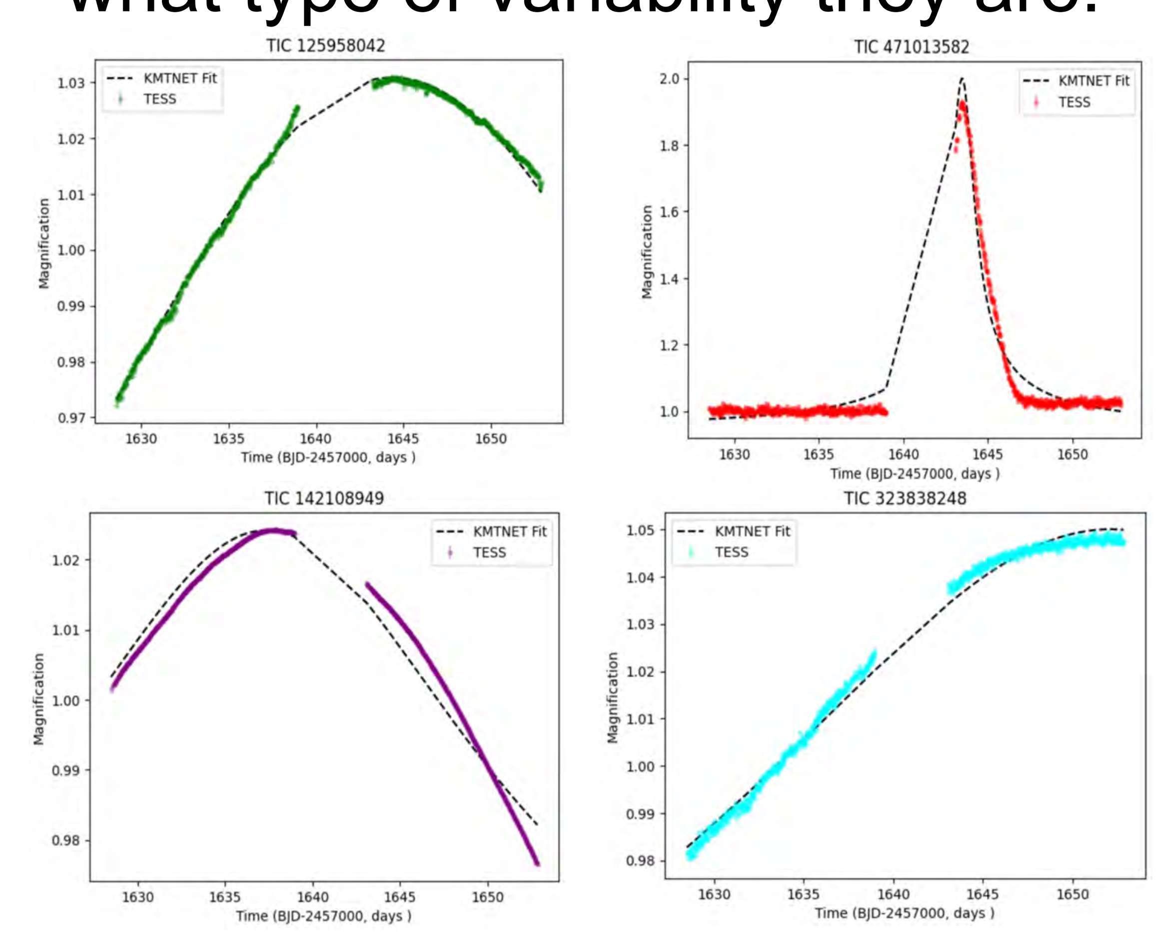
How does this algorithm work?

Instead of a single 5-parameter non-linear PSPL fit, a set of 2-parameter linear fits are fitted to the light curves.

- The function is

$$F(t) = f_1 A_j\left[Q\left(t; t_0, t_{eff}\right)\right] + f_0$$

  where A_j is magnification when $u_0 \rightarrow 0$ (j=1) and u_0 =1 (j=2).
- $F(t)$ is defined on a grid of t_0 and t_{eff} ($t_{eff} \equiv u_0\, t_E$) and is fitted to find the best parameters f_0 and f_1 .
- We use $\Delta\chi^2$ and the Von Neumann statistic η [4] to define detection as $\Delta\chi^2 > 500$ and $\eta<0.02$ (η chosen based on the simulations).
- The algorithm marks 3% of the TESS sector 12 data as candidates and these are vetted by eye to find what type of variability they are.

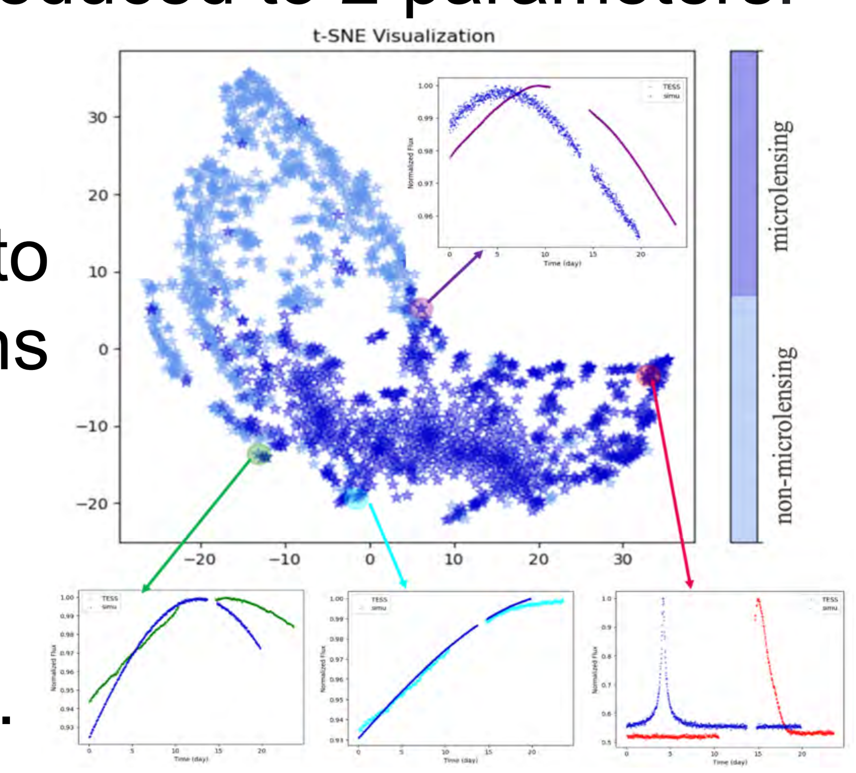


Four examples of microlensing candidates found in sector 12.

Deep Learning Model

We first use a visualization method called t-distributed Stochastic Neighbor Embedding (t-SNE) to show the TESS light curves and the simulations in a 2-parameter space. Each point on this plot is a single light curve that is reduced to 2 parameters.

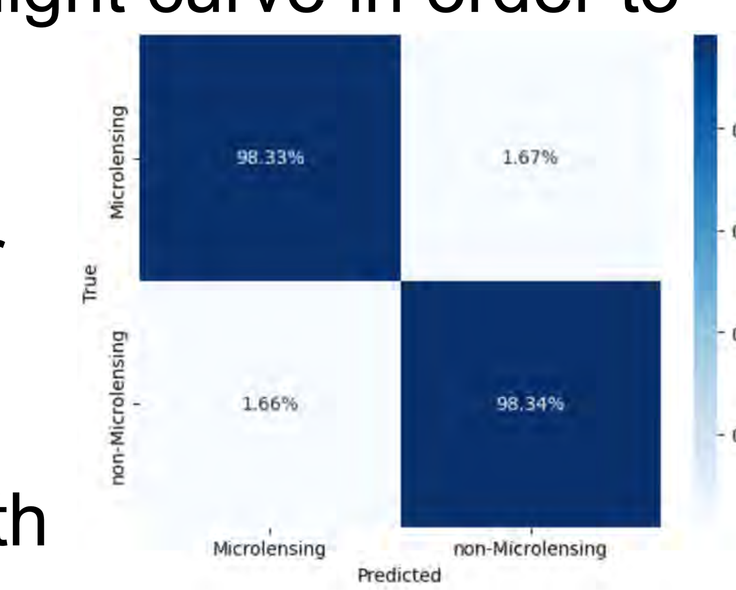
We find that TESS light curves close to the simulations in this space are in face microlensing-like variability.



Transformers: A type of deep learning model that finds relationships in sequential data like text.

We use this on light curves to find the relationships between the different segments of a light curve in order to classify them.

We have been able to recover 98% of the simulations we put in along with 2% of the TESS data labeled as microlensing and that includes lightcurves similar to what we found with the traditional method.



References

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