Exploring the Sub-Second Transient Sky with Continuous-Readout Images and Neural Networks

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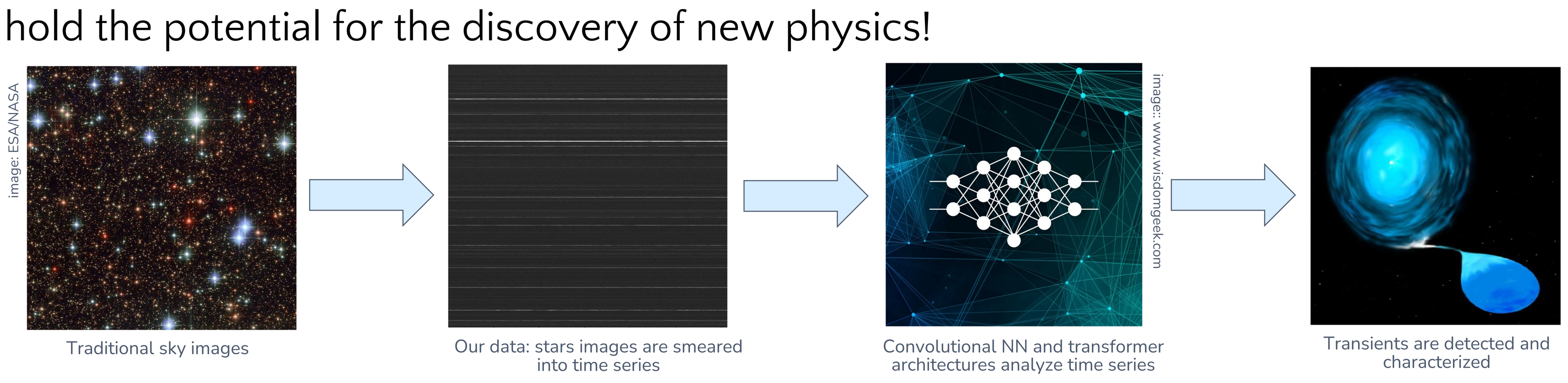
TLDR (Summary)

I am developing novel data collection and AI-aided analysis methodologies that will allow us to systematically and thoroughly investigate the dynamic universe at sub-second timescales by integrating stars along the image over time. The sub-second timescales of astrophysical variability are largely unexplored, but can reveal the nature of known phenomena by characterizing their short-term variability and even hold the potential for the discovery of new physics!



Motivation: Why care about sub-second transients?

Transient astronomy, the study of phenomena in the universe that change on human timescales, is an opportunity to discover everything from fundamental physics to the most energetic phenomena ever observed. Synoptic surveys provide opportunities find transients never before seen nor even hypothesized.

Transients are characterized by the time scale over which they vary, their "characteristic time scale", and by their energy output. **Figure 1** shows the zoo of known optical transients in a phase-space of peak magnitude – characteristic time scale. The hours-to-years portion of the graph is well explored, with many known phenomena. However, the minutes-to-fractions-of-seconds region is nearly empty. Several phenomena that are expected to vary on sub-second timescales (e.g. [2, 3] see **Fig. 2**) but observations in this space are particularly challenging .

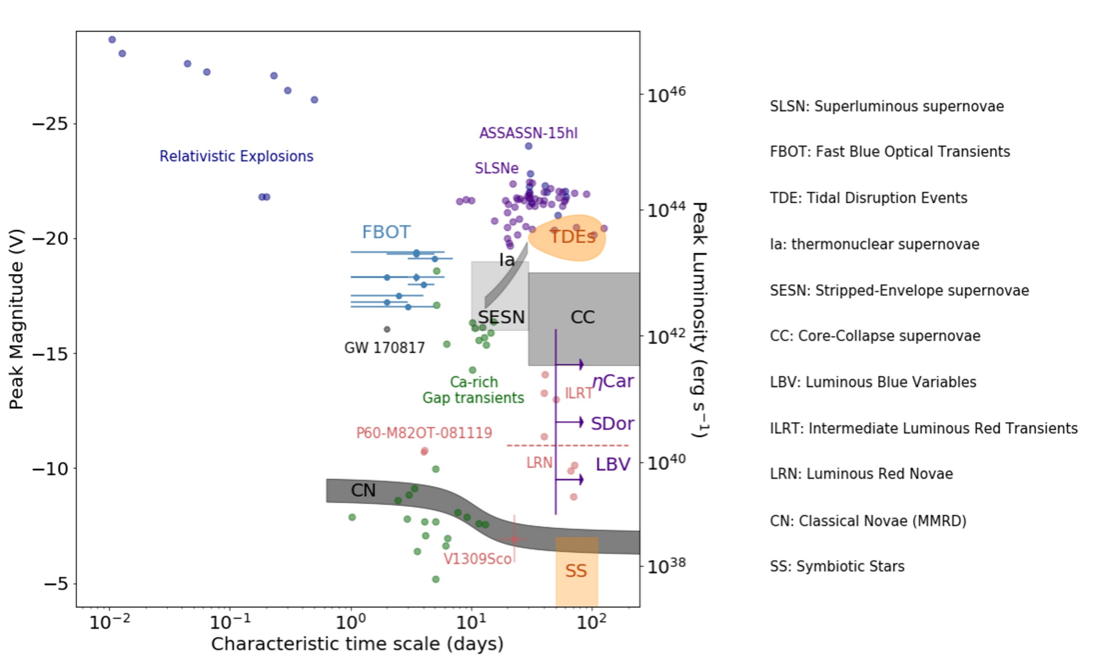


Figure 1 (modified from [1]): Known transient phenomena, categorized by characteristic timescale and peak magnitude

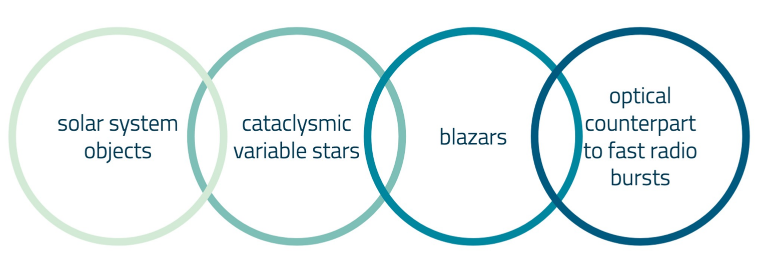


Figure 2: Expected sub-second optical transients
Solar system objects: occultations of Kuiper belt objects
Cataclysmic variable stars: episodic violent stellar bursts
Blazars: active galactic nuclei with relativistic jets
Fast radio bursts: highly energetic mysterious radio sources

Traditional observational methods cannot detect transients at this timescale.

Data: Continuous-readout images

In traditional astronomical observations, the camera shutter opens, takes in photons, closes, and then the positions and intensities of the captured light is read out. These exposure and readout cycles require seconds or minutes to complete.

However, two nontraditional observing modalities, **trailing and continuous-readout [4],** enable resolution at sub-second timescales by leaving the shutter open during slew or readout. This has the effect of integrating each astrophysical image along one spatial dimension, so that the resulting image has one time dimension and one spatial dimension (see **Fig. 3).** This methods allow us to resolve the data at second or sub-second sampling rates.

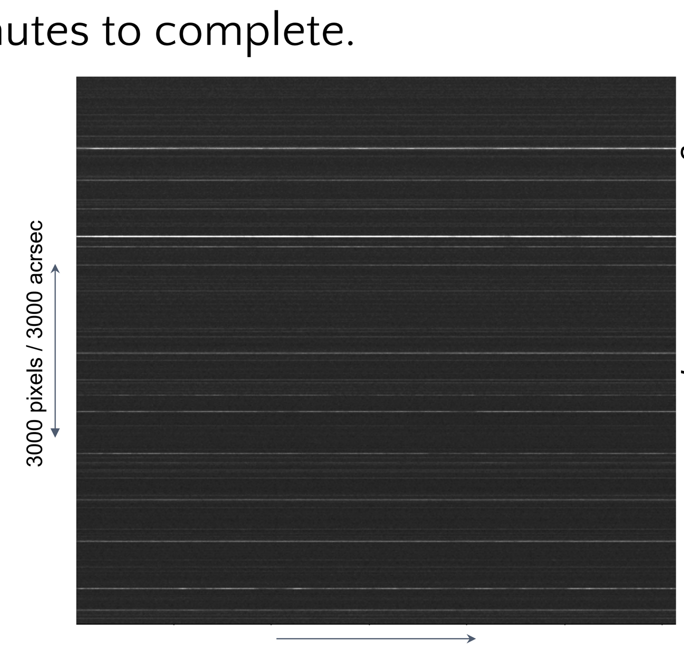


Figure 3: an example of our ZTF data

Our images were taken in continuous-readout mode at the Zwicky Transient Facility [ZTF, 5] in a special program lead by PIs Andreoni and Mahabal. The images are sampled approximately 300x per second.

450Gb dataset covers 5k star-hours sampled 300x per second

450GB of data are currently available, and the dataset will triple in the next few years.

Trailing images while slewing has been proposed for the upcoming Vera C. Rubin LSST [6], leading to a 10ms sampling rate.

Acknowledgements

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Methodology: Sliding-window CNN

Continuous-readout images require custom-made analysis tools. Our planned methodology includes the application of convolutional neural networks (CNNs) [8] and transformers [9]. Here we present preliminary results for our CNN-based analysis.

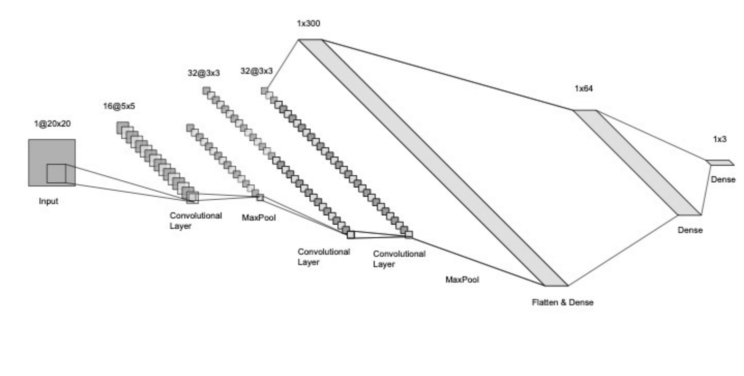

Figure 4: CNN architecture

Sliding-window CNN model:
Our sliding-window CNN scans the images, classifying each pixel in the context of a larger square window of pixels around it and looking for pre-determined patterns of transient behavior (brightening and dimming). **For each pixel, the CNN outputs the probability that it belongs to each of three classes: background, star streak, or star streak with transient.**

Training data preparation:
We generated a synthetic transient dataset by implanting brightening events in 200 star streaks. Each implantation is generated by multiplying the star-streak flux by as a gaussian profile increase:

$$F * ((A-1) * (e^{-(x-M)^2/(2\sigma^2)}) + 1)$$

F is the initial streak flux, *M* is the location of the transient along the streak, *A* is the brightening amplitude, and *σ* is the transient's duration.

Table 1

Parameter	Range	Distribution
A	2 to 10	30% 2's, 30% 3's, 20% 4's, 10% 6's, 10% 10s
M	-5 to 25	Random
σ	3	-

See **Fig. 5** for an example and **Table 1** for the distribution of parameters in our implantations. **Future work will include increasing the diversity of transient morphologies.**

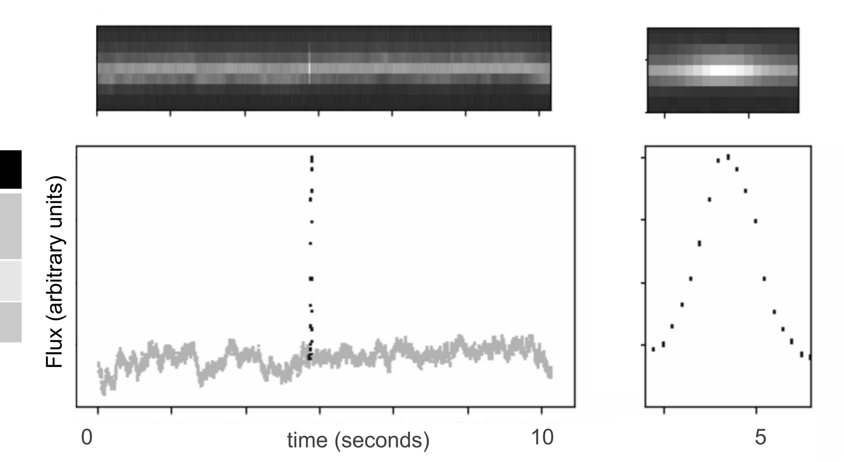

Figure 5: Example of a transient implantation.
Top: the implanted streak (L), zoomed in (R)
Bottom: resulting time series from aperture photometry

Preliminary results

An example of the CNN's output is shown in **Fig 6. All transients in the image segment are detected correctly.**

Figure 6: Example of our CNN's successful detections of implanted transients

To go from probabilistic classification to detection, we set two thresholds:
- *α*: the minimum absolute transient probability
- *r*: the minimum ratio of class probabilities

Varying these thresholds, we can produce Precision and Recall surfaces. **Our preferred model achieves a Recall of 100% and Precision of 83% with the parameters *α=0.68* and *r=2*.**

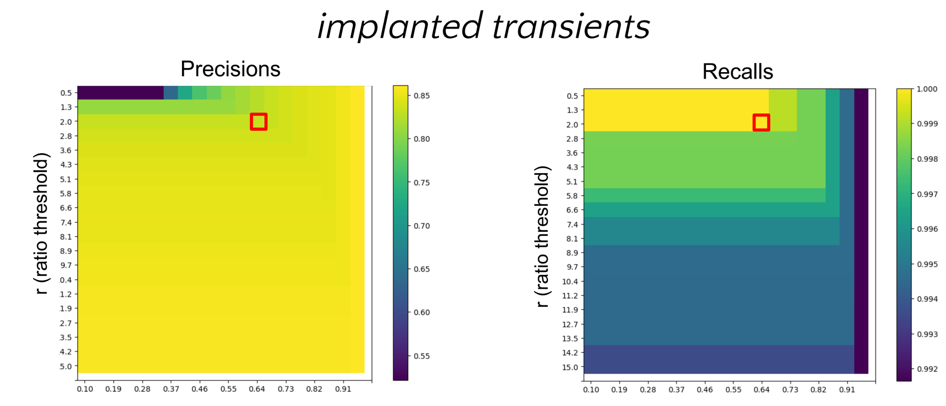

Figure 7: Precision & Recall surfaces obtained by varying classification thresholds. Red: our preferred parameters.
Precision: # true positives labels / # all positive labels
Recall: # true positive labels / # all implanted transients

Future work: Transformers

Transformers [9] are a class of neural networks for language prediction based on the attention mechanism, which enables variable correlations to be established between elements of a sentence. The encoder element of the transformer can enable classification of multivariate time series.

Continuous read-out sky images are especially suited to transformer based analysis as every star therein is a multivariate time series. **Using transformers would allow us to extend our detection of transients to a characterization of their transient behavior.**

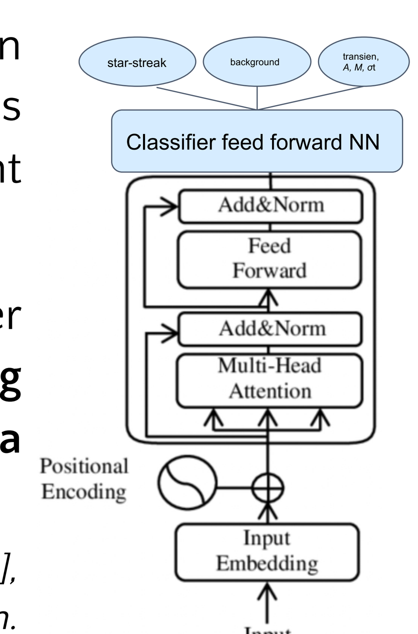

Figure 8: Modified transformer architecture: the encoder is identical to [9], connected to a feedforward NN with a 3-neuron output layer for classification.

References

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