



# Discovering Fast Optical Transients with Continuous Readout-Mode Imaging

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# AGENDA

Questions & interruptions  
welcome!

- Overview of fast transients
- My data
  - Continuous-readout mode survey data from the Zwicky Transient Facility
- Analysis methods
  - Machine learning, image preprocessing and postprocessing
- Findings and results



astrophysical

# TRANSIENTS:



astrophysical

# TRANSIENTS:

anything whose brightness changes on  
human-observable timescales



4 days

GIFRUN.COM  
CAASTRO

Credit: CAASTRO/Swinburne Astronomy Productions



astrophysical

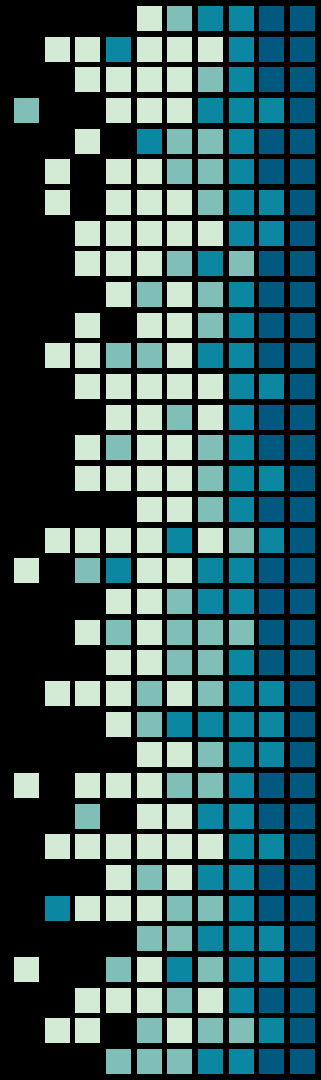
# TRANSIENTS:

often extreme phenomena that can test  
fundamental physics at a higher energy scale  
than we could ever see on Earth



## Neutron Star Merger (artist's interpretation)

<https://svs.gsfc.nasa.gov/12740>





astrophysical

# TRANSIENTS:

a realm where it is a possibility to discover  
new and entirely unexpected phenomena



# Discovery examples, old and new



"Bell Burnell spotted an object that appeared to be flickering every 1.3 seconds; this pattern repeated for days on end...'It had to be some new kind of star, not seen before,' she said." (1967)

<https://www.space.com/38916-pulsar-discovery-little-green-men.html>

"The first FRB, the Lorimer Burst, was discovered in 2007...its inferred distance was a million times greater [than pulsars], indicative of a new class of object."

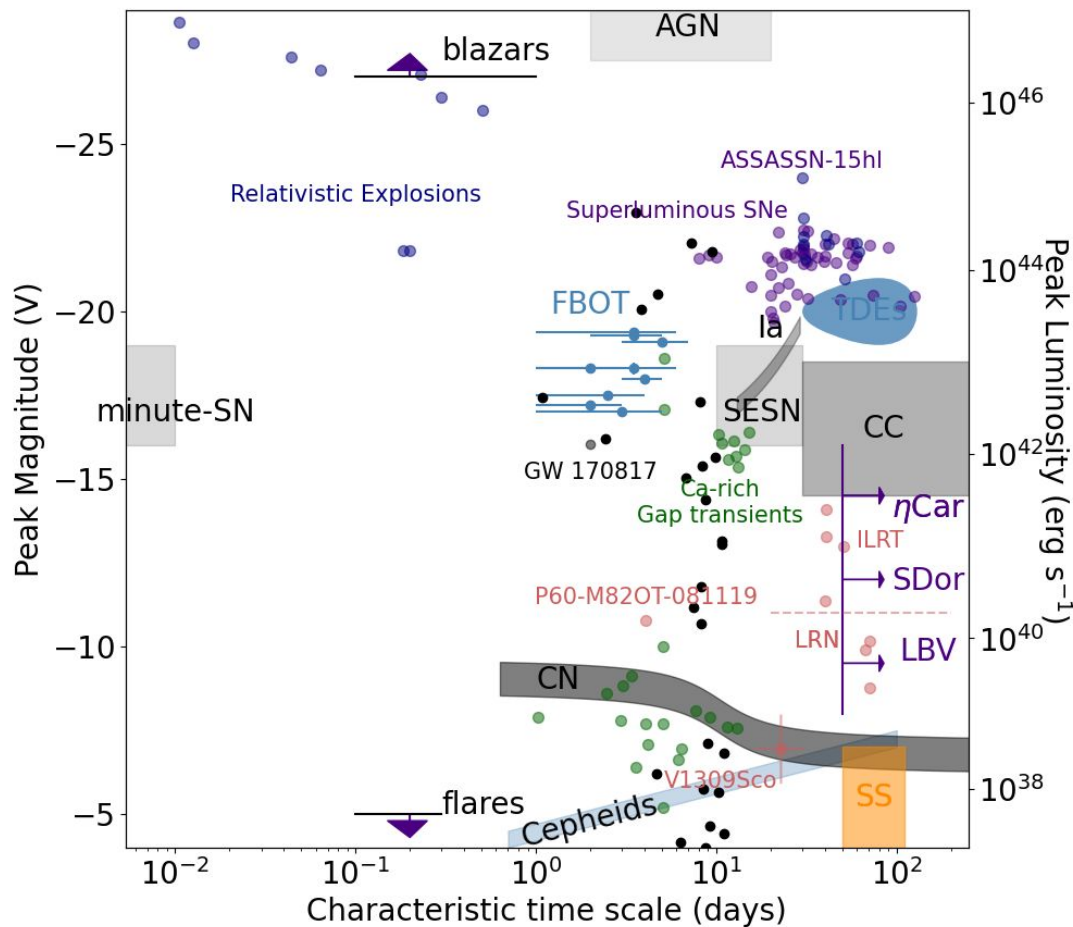
<https://www.science.org/doi/10.1126/science.abj3043>

# Most Known Optical Transients, 2024

credit:  
Federica Bianco

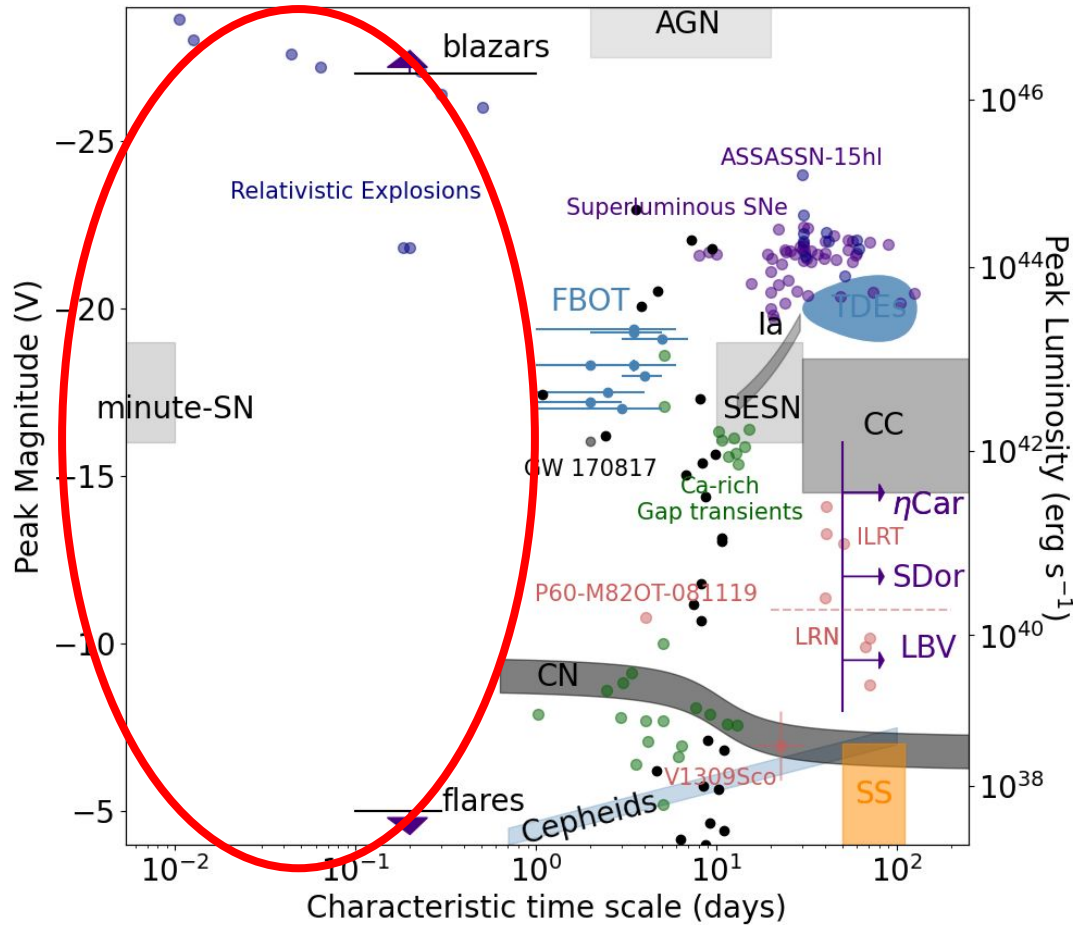
10

2024



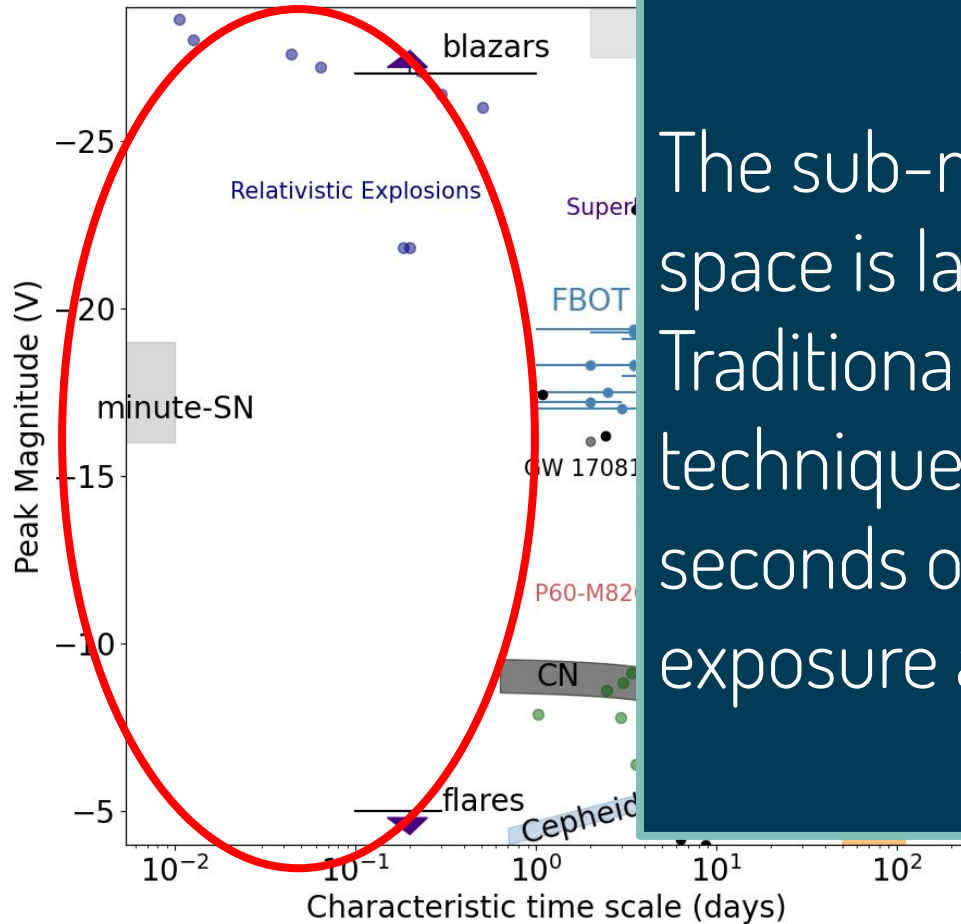
TDE: Tidal Disruption Events  
CC: Core-Collapse supernovae  
Ia: thermonuclear supernovae  
SESN: Stripped-Envelope supernovae  
LBV: Luminous Blue Variables  
LRN: Luminous Red Novae  
CN: Classical Novae (MMRD)  
ILRT: Intermediate Luminous Red Transients  
SS: Symbiotic Stars

# Most Known Optical Transients, 2024



credit:  
Federica Bianco

# Most Known Optical Transients, 2024



The sub-minute parameter space is largely unexplored. Traditional imaging techniques require seconds or minutes for exposure and readout.

# Expected to have second or sub-second variability:

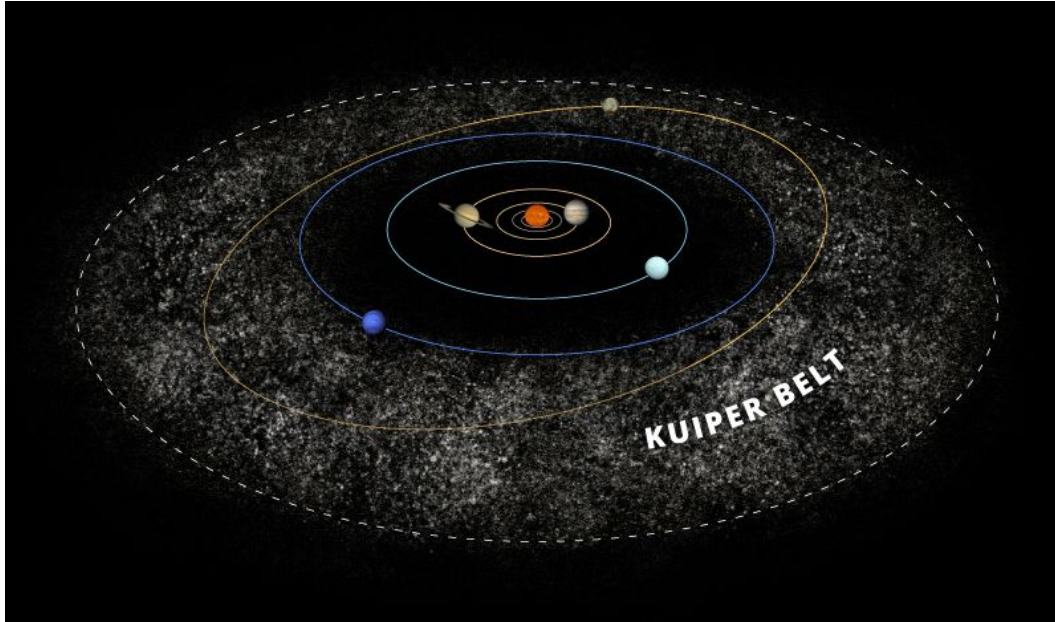
Solar system  
objects  
(Nihei et al  
2007)

Accretion on  
compact  
objects  
(Bruch 2021)

Blazars  
(Raiteri et al  
2021)

Optical  
counterpart  
to fast radio  
bursts  
(Chen, Ravi,  
and Lu, 2020)

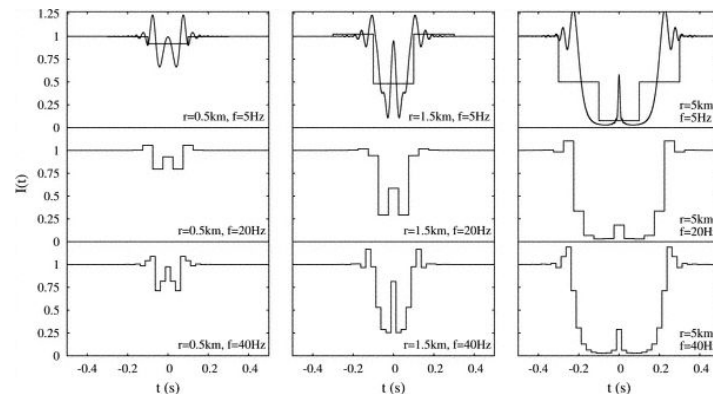
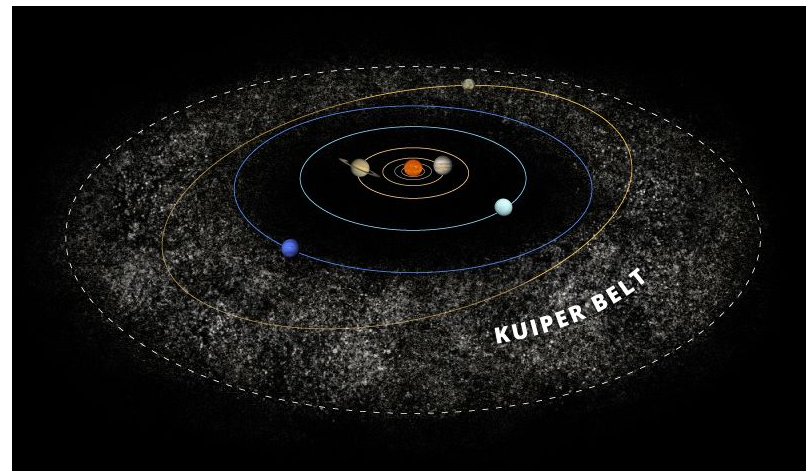
# Solar System Objects



<https://solarstory.net/img/articles/big/kuiper-belt-illustration.jpg>

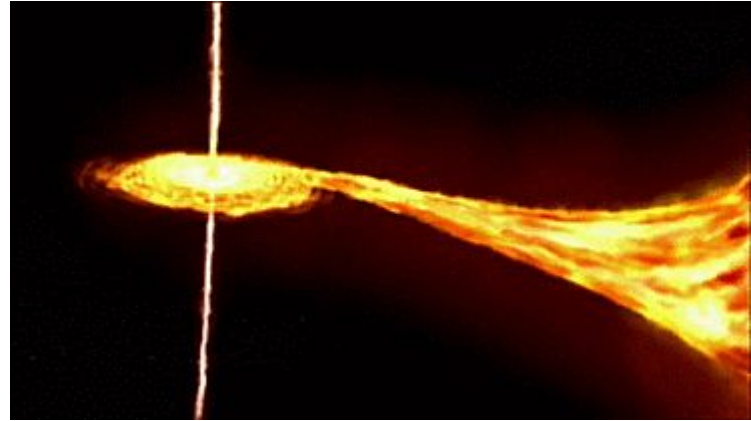
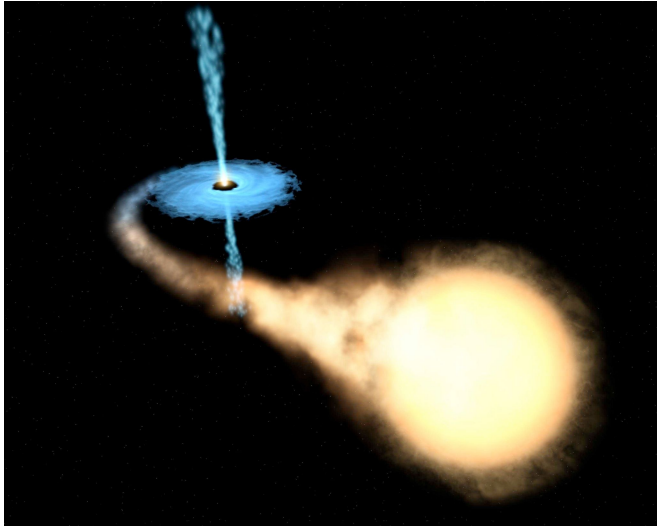
# Solar System Objects

- The passage of Kuiper Belt objects in front of stars causes subsecond brightness decreases, with structure on the millisecond-level scale
  - Small Kuiper Belt-distance objects produce characteristic diffraction patterns (Nihei+ 2007)



Kuiper Belt (<https://solarstory.net/img/articles/big/kuiper-belt-illustration.jpg>);  
Occultation diffraction patterns at various samplings (Nihei+ 2007)

# Accretion on Compact Objects

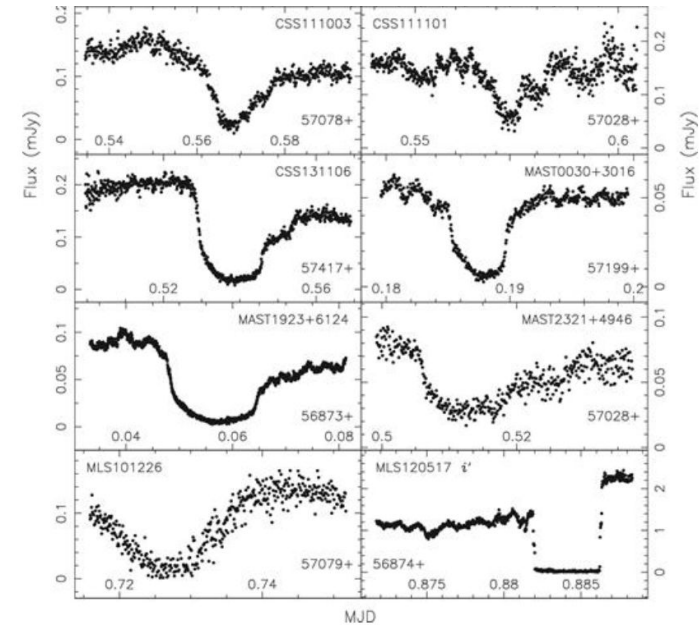
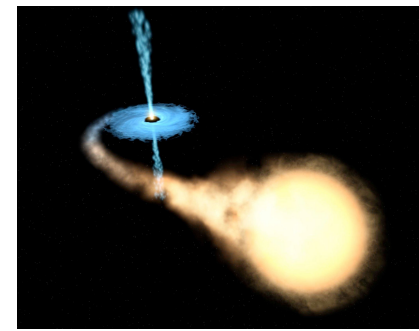


<https://aasnova.org/wp-content/uploads/2018/11/fig1-4.jpg>  
<https://i.pinimg.com/originals/2f/cc/e0/2fcce01591c7ab3714d583a6d8d3e360.gif>



# Accretion on Compact Objects

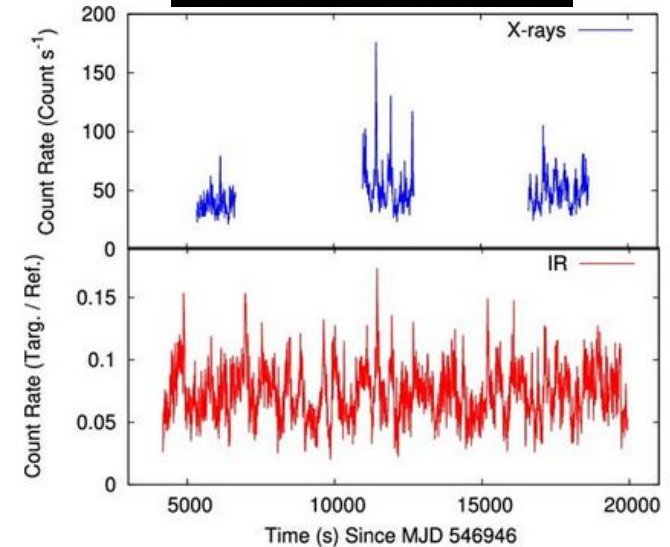
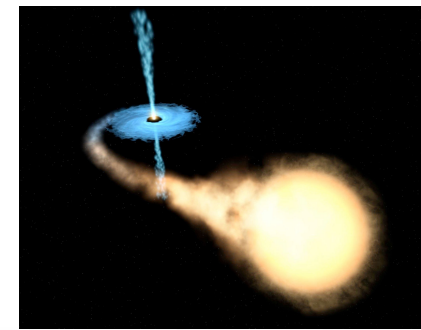
- Well studied in high energy; limited in optical
- Interesting rapid timescales in Cataclysmic Variables from tens of minutes for eclipses (Hardy+2016) to seconds for quasi-periodic oscillations (Warner+2003)



<https://aasnova.org/wp-content/uploads/2018/11/fig1-4.jpg>  
Eclipses (Hardy+2016)

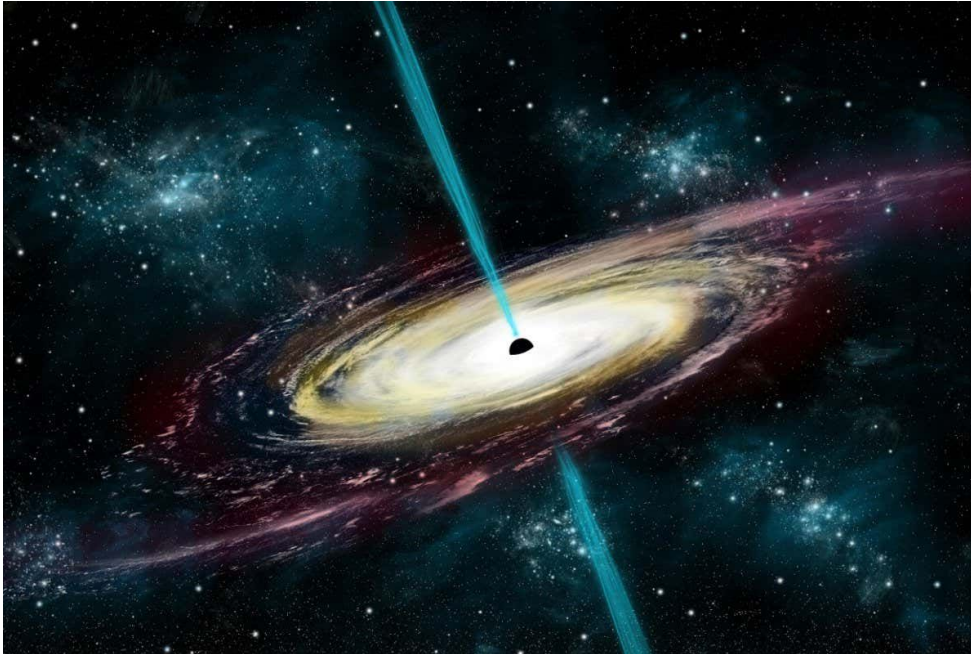
# Accretion on Compact Objects

- Well studied in high energy; limited in optical
- Interesting rapid timescales in Cataclysmic Variables from tens of minutes for eclipses (Hardy+2016) to seconds for quasi-periodic oscillations (Warner+2003)
- Optical reprocessing in X-ray binaries, timescales of ~seconds (Igl+2023)



X ray and IR variability of the black hole x-ray transient GX 339-4 (Vincentelli+2018)

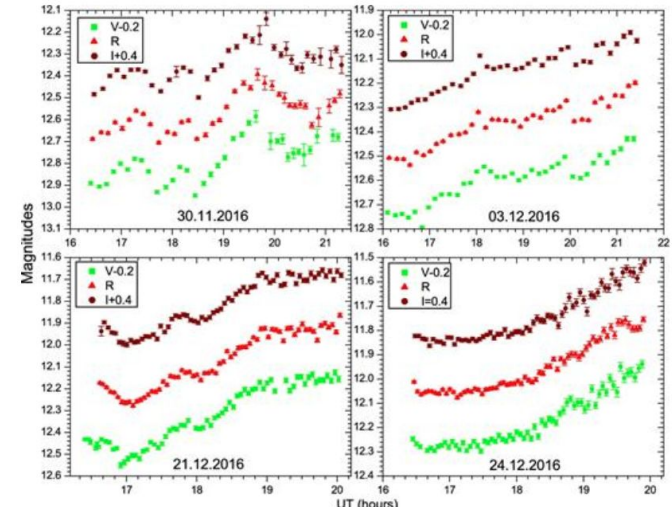
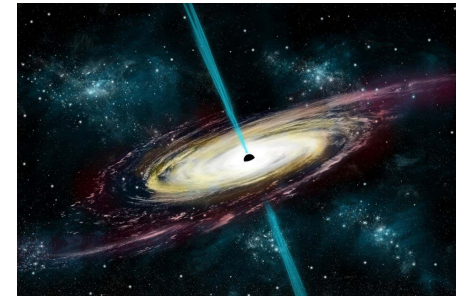
# Blazars



[https://images.ewscientist.com/wp-content/uploads/2022/11/21230533/SEI\\_134642962.jpg](https://images.ewscientist.com/wp-content/uploads/2022/11/21230533/SEI_134642962.jpg)

# Blazars

- Blazars can show intra-night variability 'sometimes of  $\sim 0.5$  mag within several hours' (Bachev+2017)
  - Variability on time-scales  $< 5$  hrs is likely caused by intrinsic energetic processes involving emitting regions, likely jet substructures, with dimension less than about  $10^{-3}$  pc (Raiteri+ 2021)



[https://images.newscientist.com/wp-content/uploads/2022/11/21230533/SEI\\_134642962.jpg](https://images.newscientist.com/wp-content/uploads/2022/11/21230533/SEI_134642962.jpg)

Blazar variability from Belogradchik Observatory (Bachev+2017)

# Optical Counterpart to Fast Radio Bursts

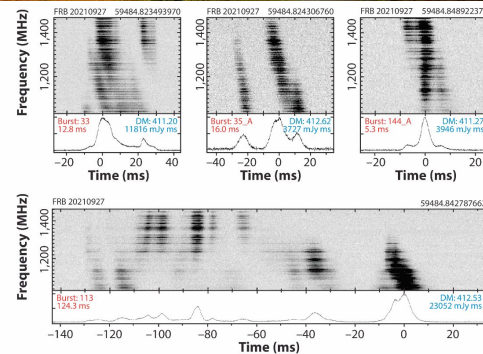


<https://earthsky.org/upl/2018/01/fast-radio-burst-Green-Bank-e1515608387676.jpg>



# Optical Counterpart to FRBs

- The only known multiwavelength FRB counterpart was an x-ray burst from the only Galactic FRB (Zhang 2024)
  - an optical counterpart could arise from inverse compton scattering if the FRB environment involves a neutron star with an extremely strong magnetic field and an extremely fast spin, or an extremely young supernova remnant surrounding the FRB source (Yang+ 2019)



Zhang B. 2024  
Annu. Rev. Nucl. Part. Sci. 74:89–117

Repeating FRB  
(millisecond-timescale) light  
curves in radio (Zhang 2024)

# PROBLEM

- Traditional optical observational methods cannot access sub-second timescales.
- Instrumentation built specifically for astrophysical observations on sub-second timescales exists, but it is rare, and often prohibitively expensive.



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# SOLUTION

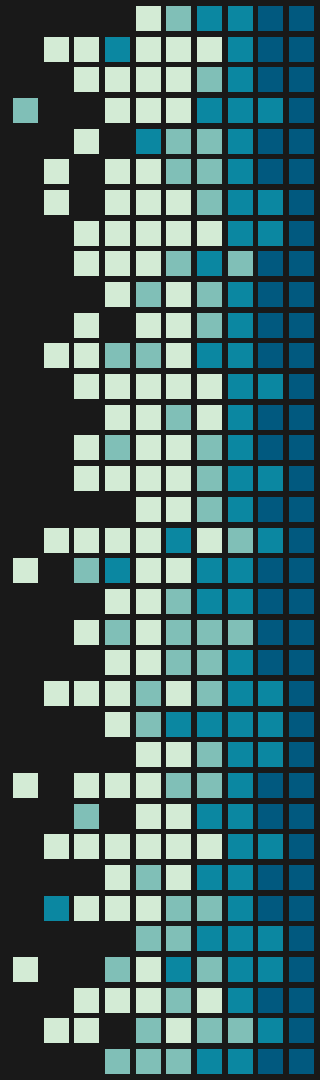
- Modified observing modes with traditional cameras, like trailing and continuous-readout, can enable observations as fast as millisecond timescales on most cameras.

Howell and Jacoby 1986  
Bianco et al 2009



# “CONTINUOUS-READOUT MODE” TIME SERIES DATA

Unique observation mode with time  
on the x axis, to allow view of  
millisecond-level structure



## Bucket Brigade CCD Analogy

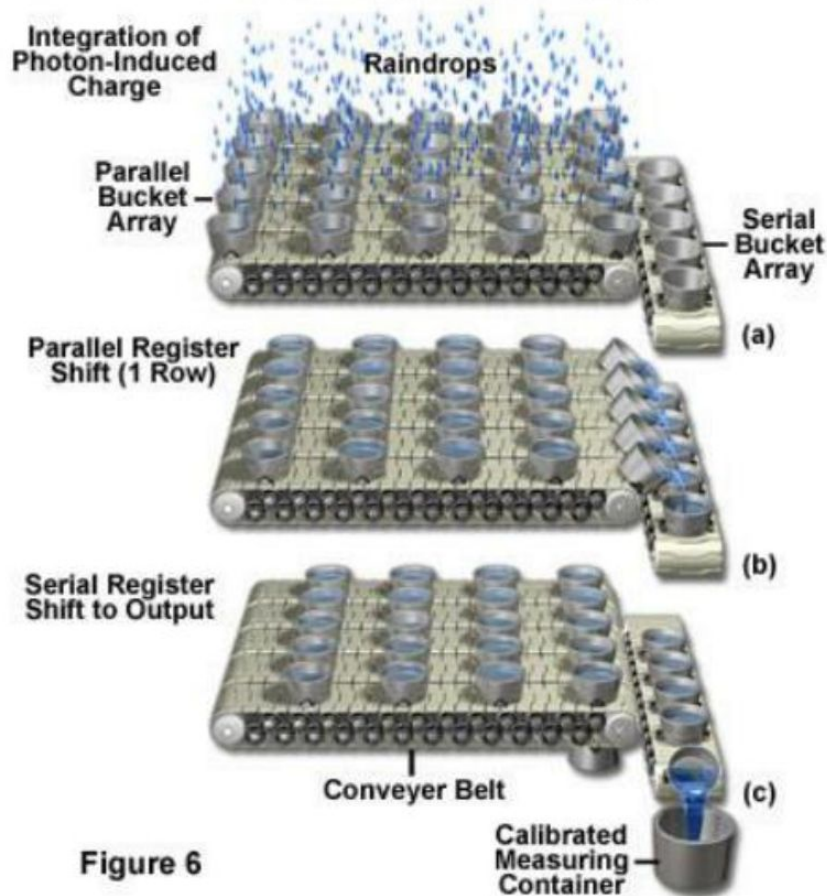
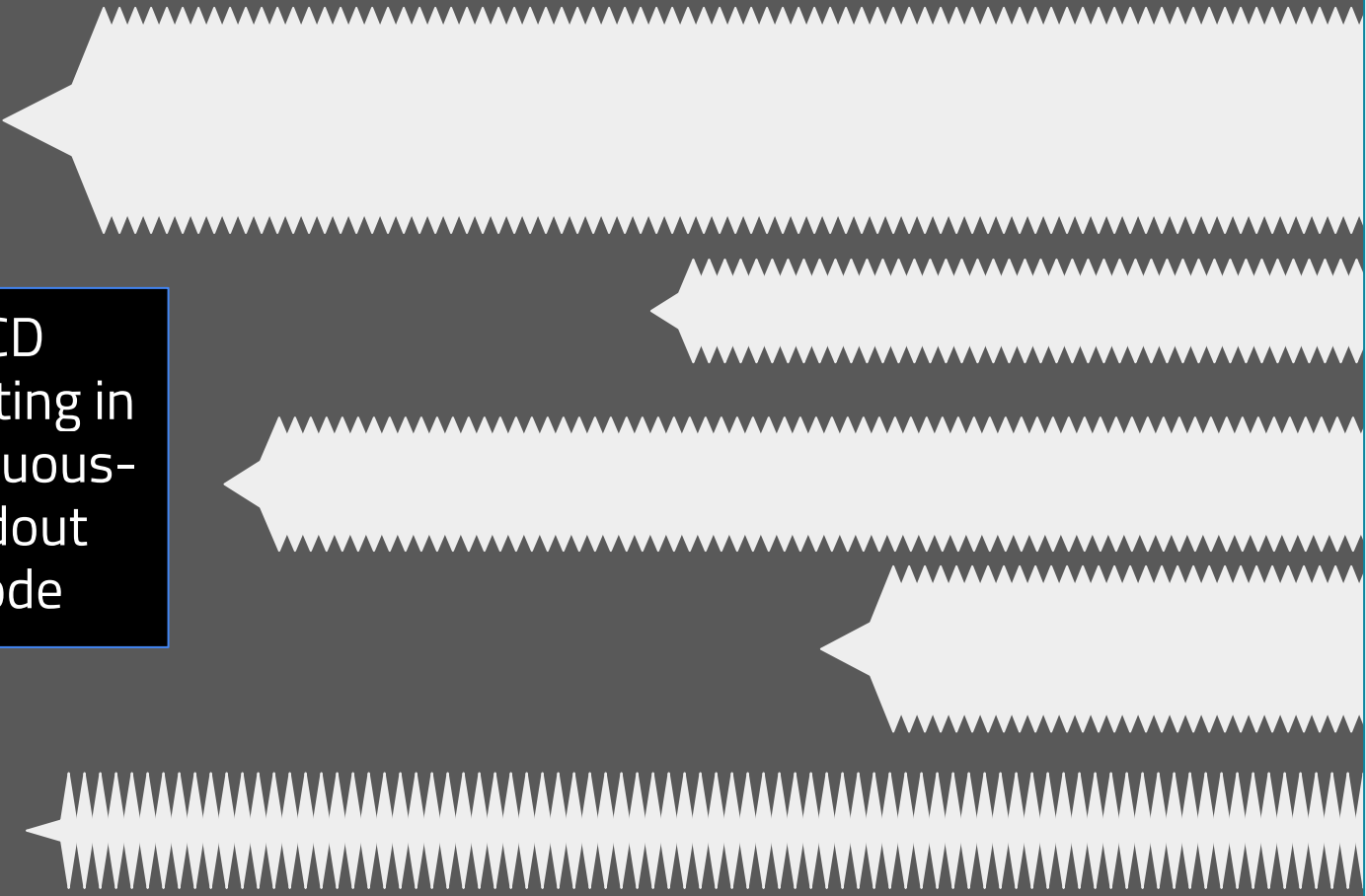


Figure 6

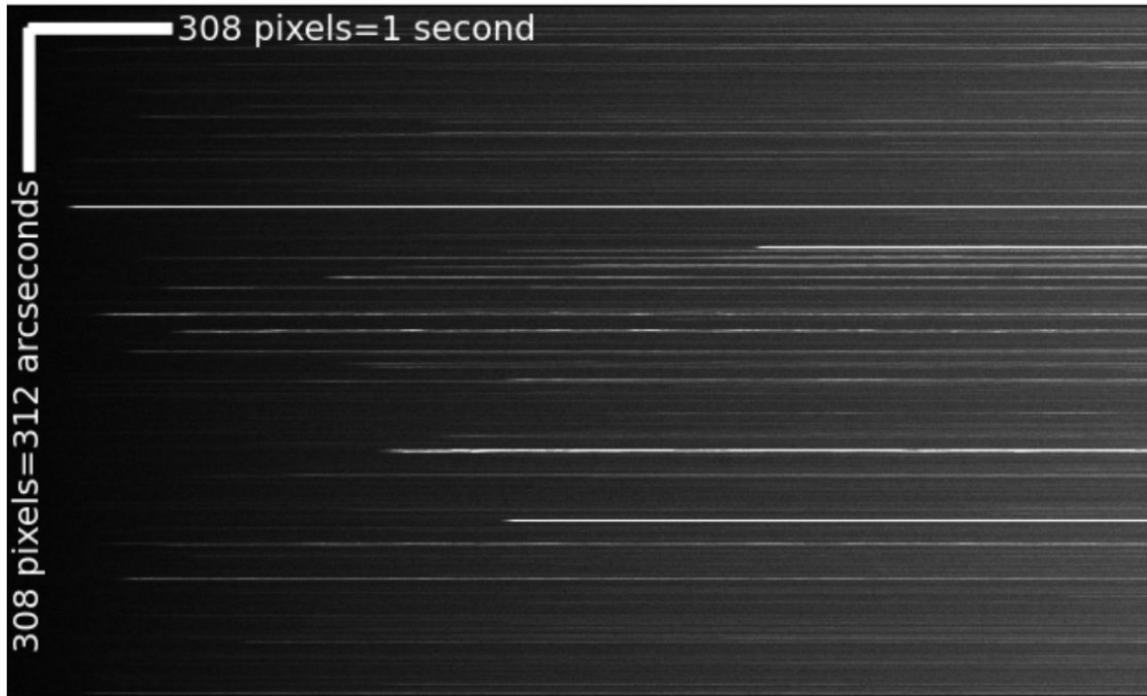
How a CCD  
works

CCD Detectors in High-Resolution  
Biology. Jian Guan 6-28-2013

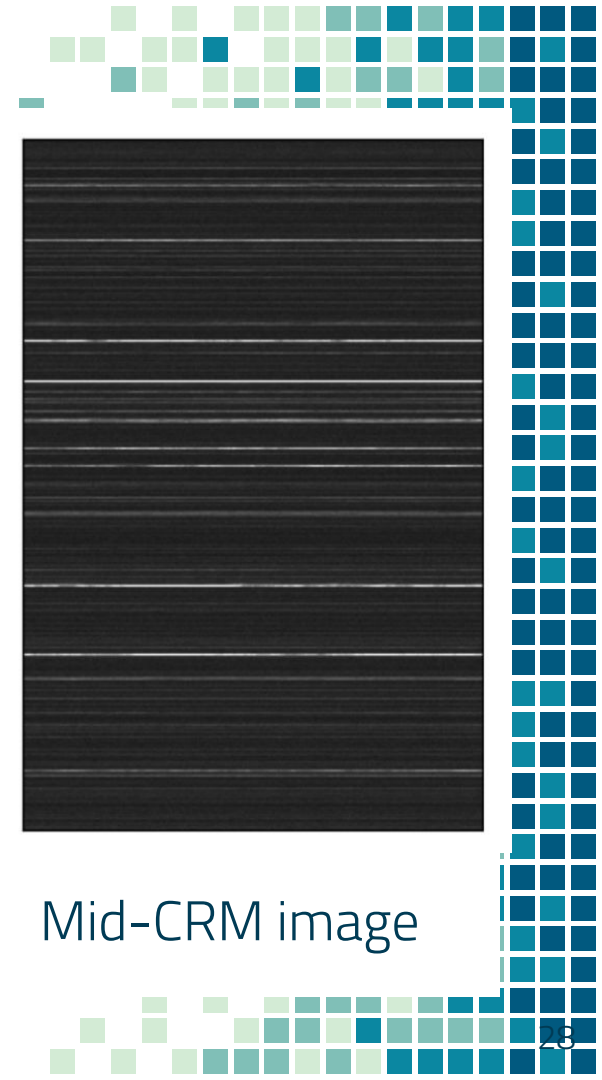


CCD  
operating in  
continuous-  
readout  
mode

Charges  
read out  
here

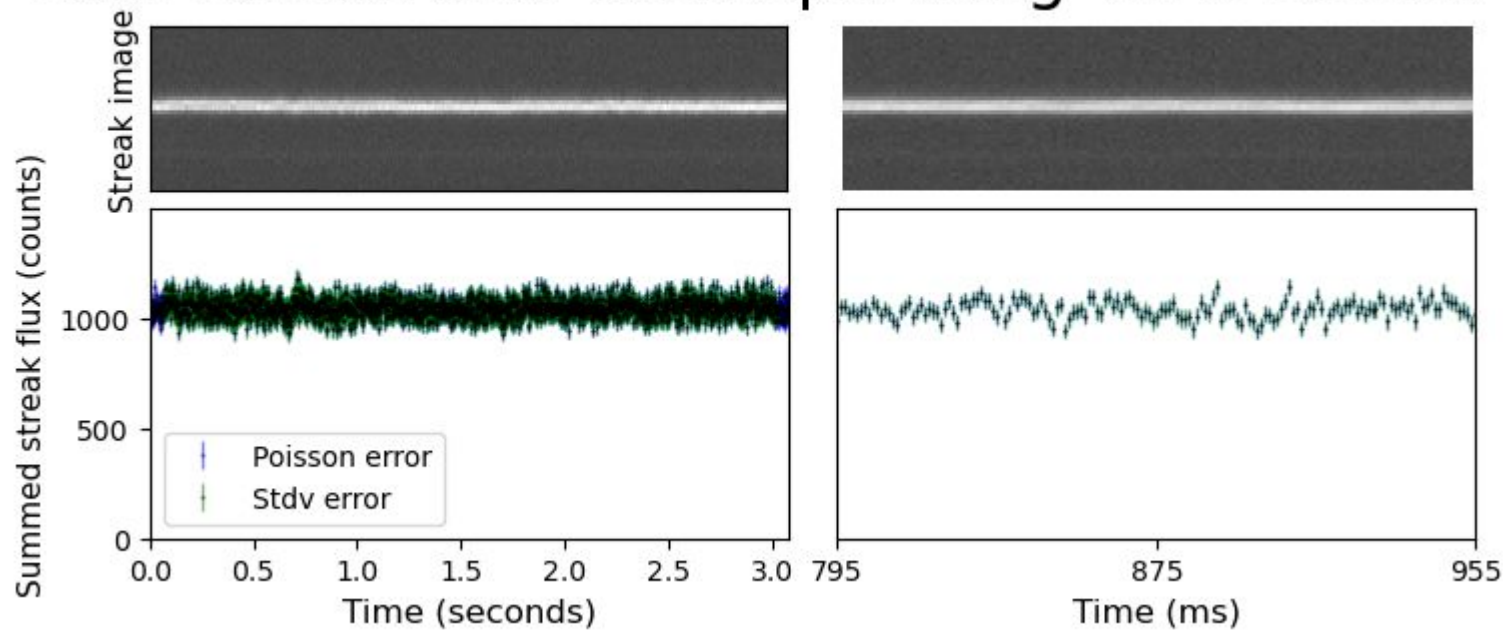


Beginning of continuous-readout mode (CRM)



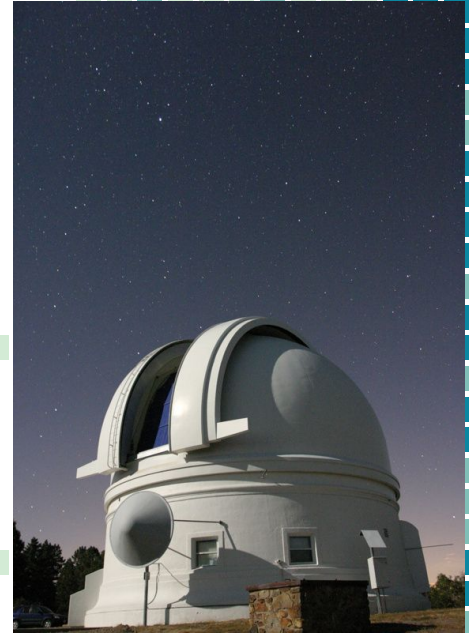
Mid-CRM image

# Star Streak and Corresponding Time Series



# The Continuous-Readout Mode ZTF Survey

- Our group collected images in continuous-readout mode from 2022-2024 at the Palomar Telescope Samuel Oschin robotic telescope (P48)
- It was a special program of the Zwicky Transient Facility (ZTF)



Bellm+ 2018  
[https://www.nsf.gov/news/mmg/  
media/images/48night\\_h.jpg](https://www.nsf.gov/news/mmg/media/images/48night_h.jpg)

371 GB

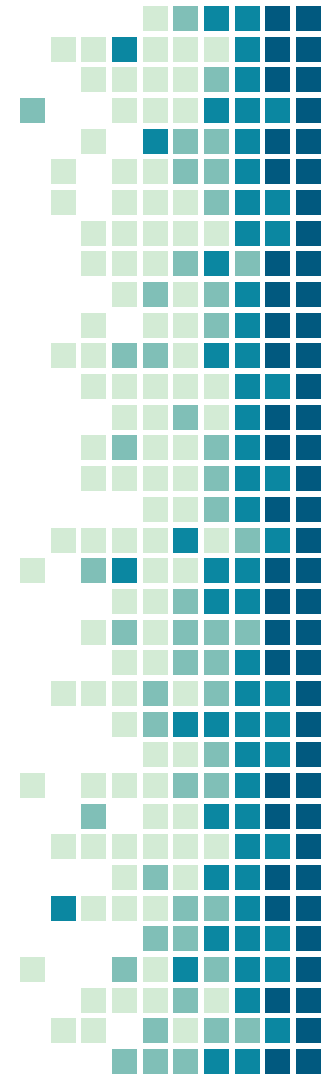
of data, containing

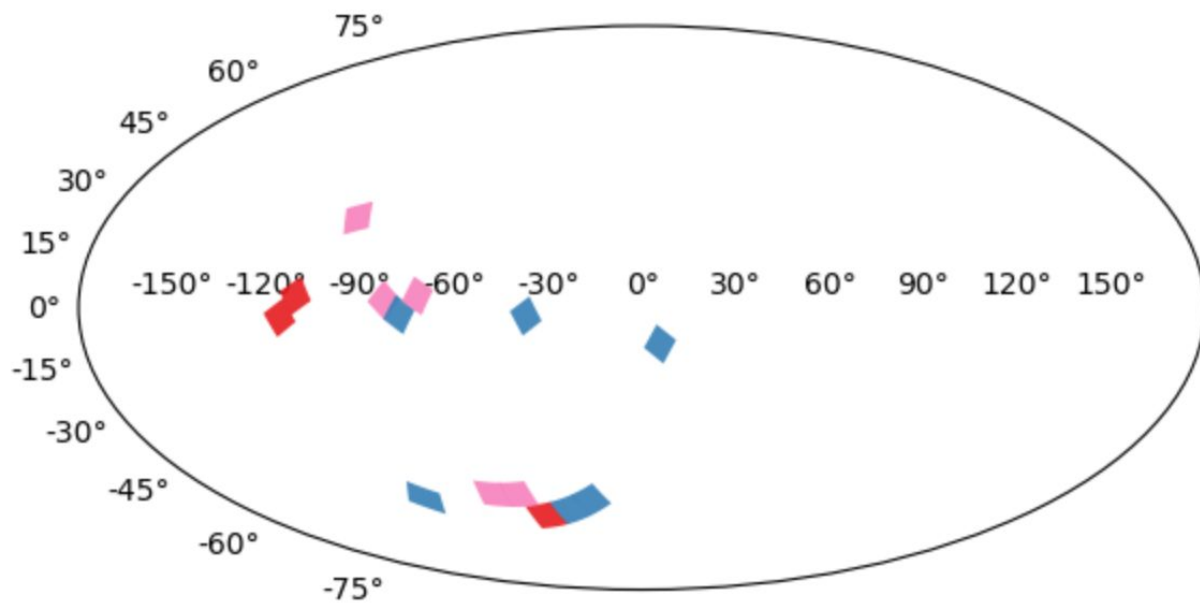
525 star – hours

collected as of 10-26-2022

600x/second

sampling rate





Sky map of  
observed  
fields.

Pink: training  
data

Red: inference  
data

Blue: observed

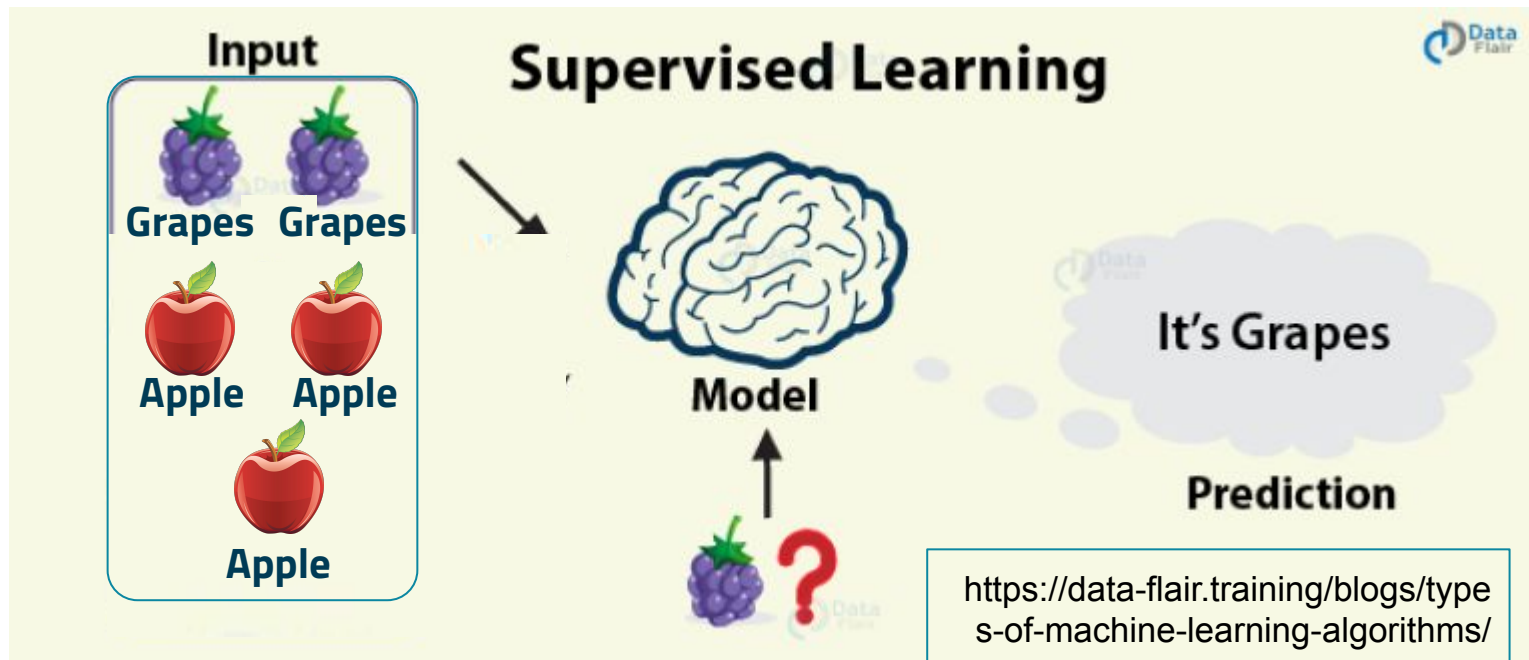
In this pilot work, I analysed a subset of our data:  
43,320 star-streaks or 120 star-hours, from  
68 observing runs



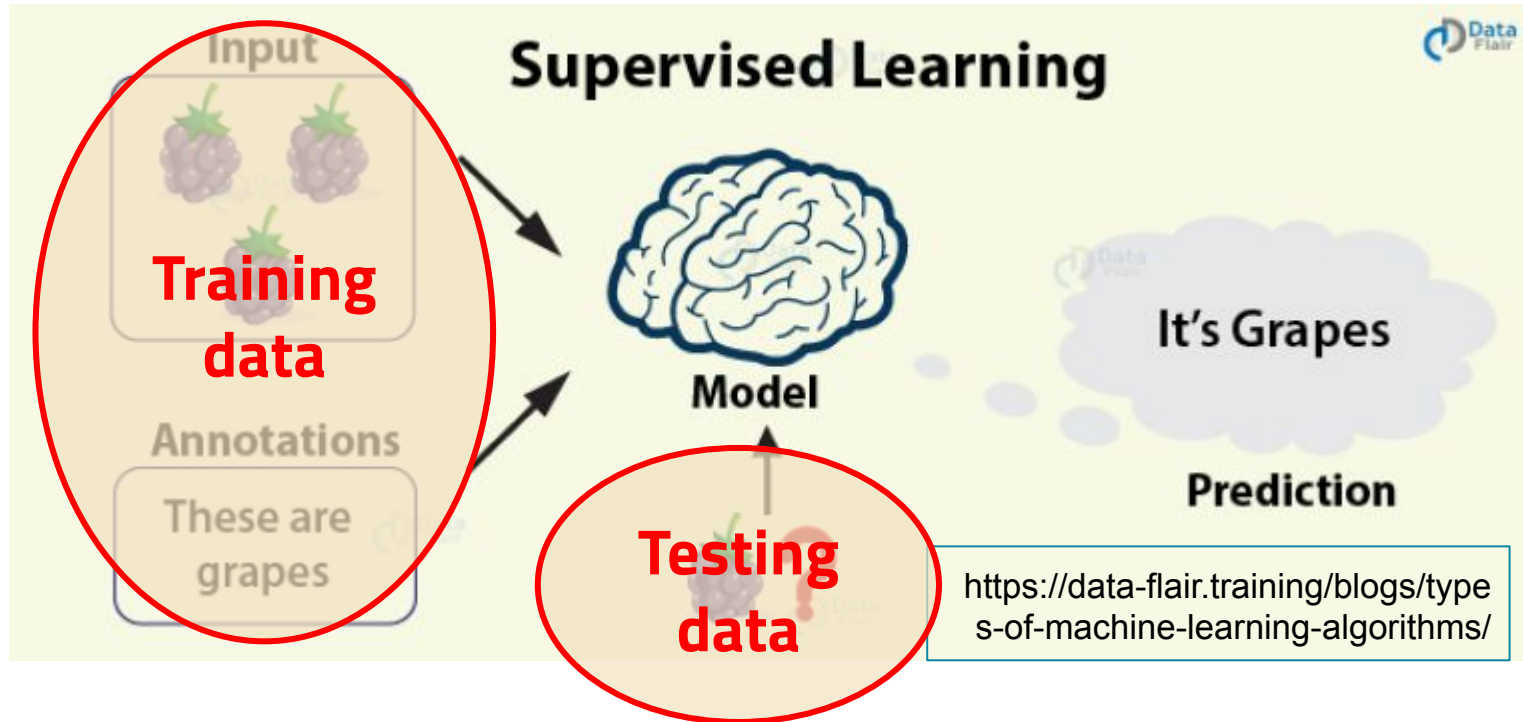


Custom-built analysis tools  
are necessary to analyze  
continuous-readout mode  
data

# Supervised learning



# Supervised learning



# Neural networks

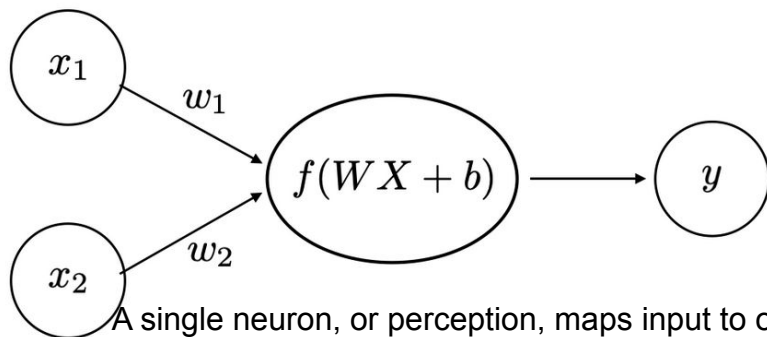
## What they do:

- handle large amounts of data
- find subtle and rare patterns within

## How they do it:

- given examples of input-target pairs, they are “trained” to associate input features with target labels

consist of sequential layers of interconnected nodes, called “neurons”, with trainable weights



A single neuron, or perception, maps input to output by a linear transformation and an activation function

Gurney 2018.

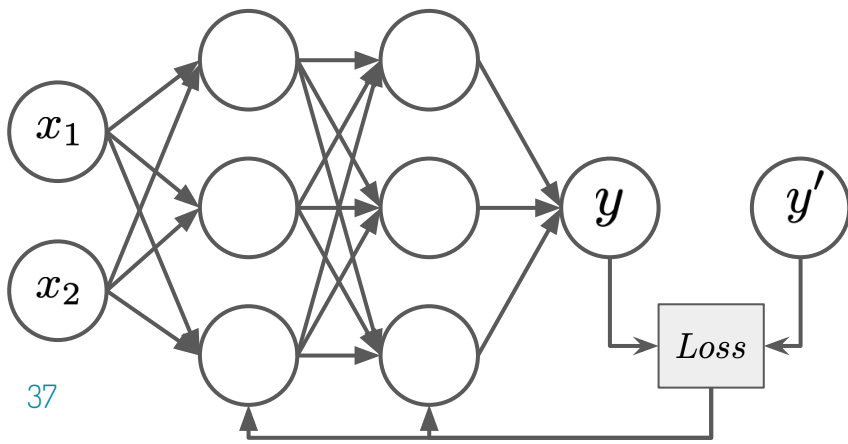
# Neural networks

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Gurney 2018.

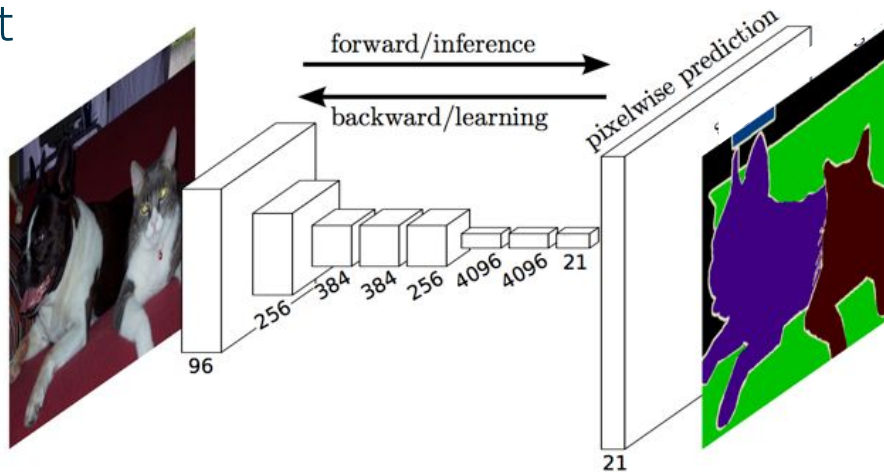
# Convolutional neural networks

## What they do:

- excel at recognizing patterns in image-like data
- learn patterns in adjacent input features

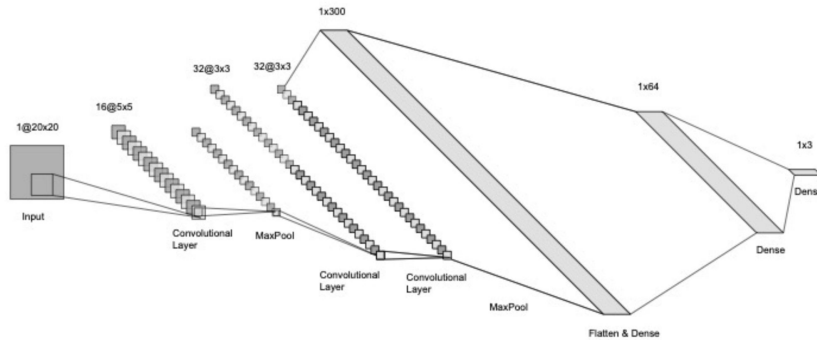
## How they do it:

- use learnable convolutional kernels as neurons



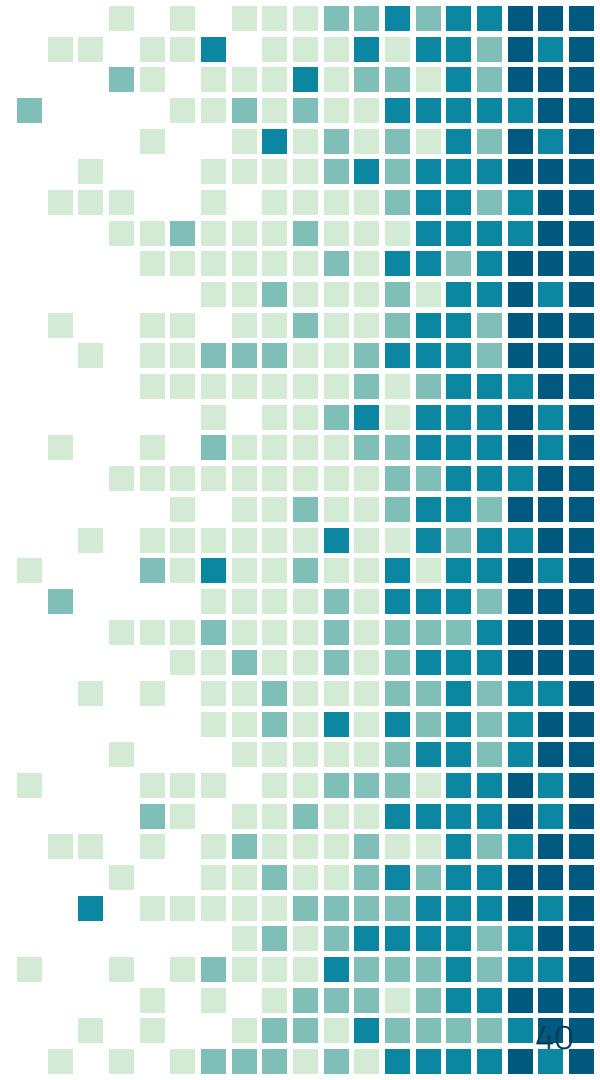
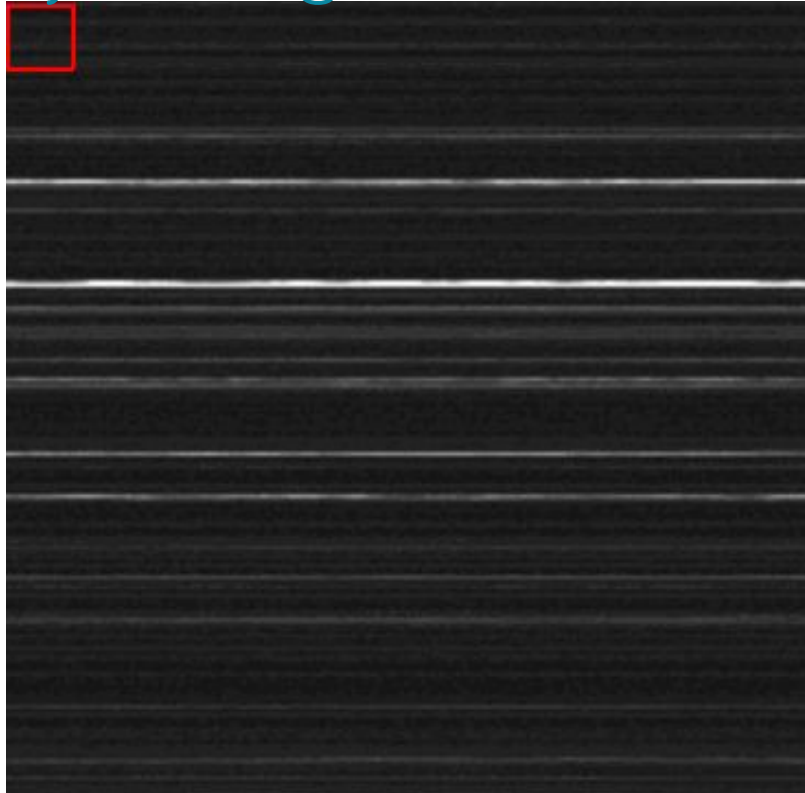
Li+ 2021.  
Long+ 2014.

# My Sliding-Window CNN



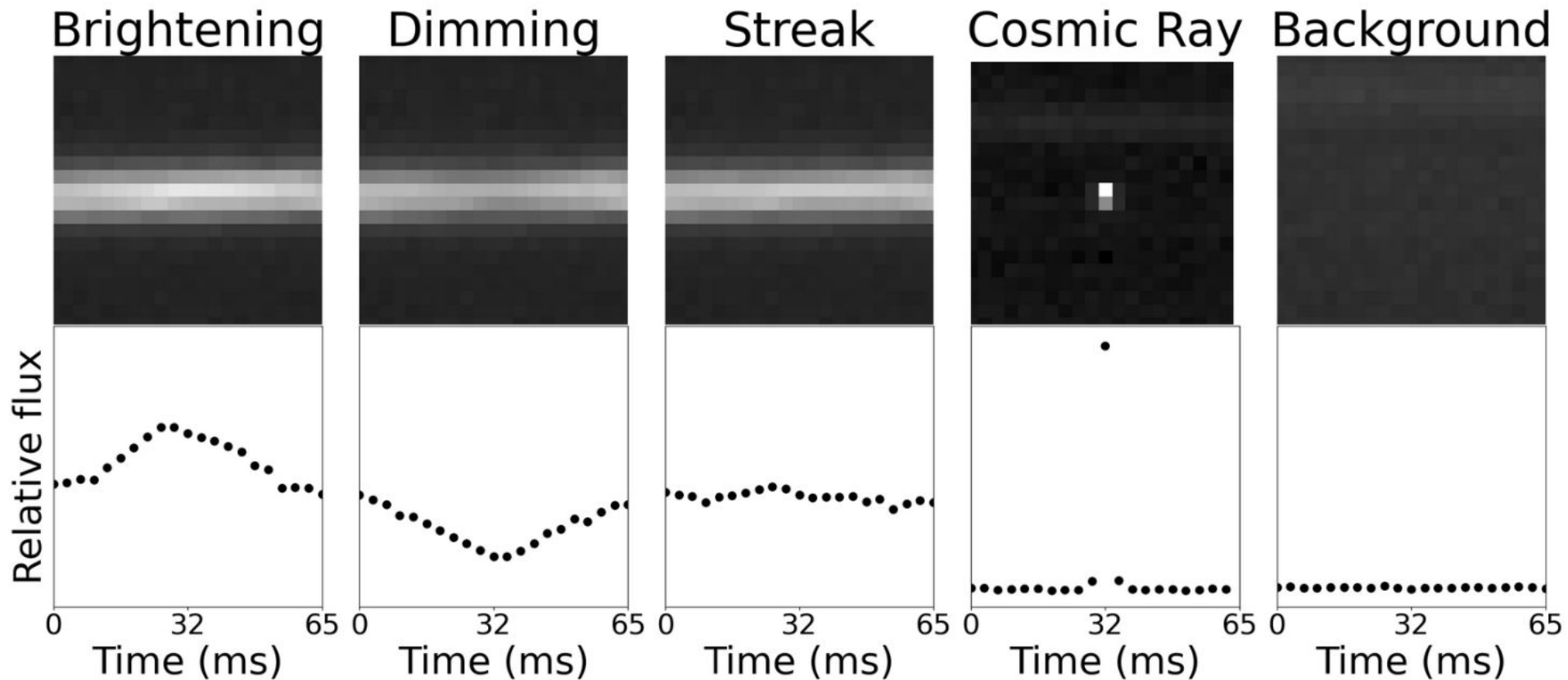
- Classifies each pixel as background, star streak, brightening transient, dimming transient, or cosmic ray
- in the context of a square window of pixels around it

# My Sliding-Window CNN





I trained the CNN using five possible input phenomena:

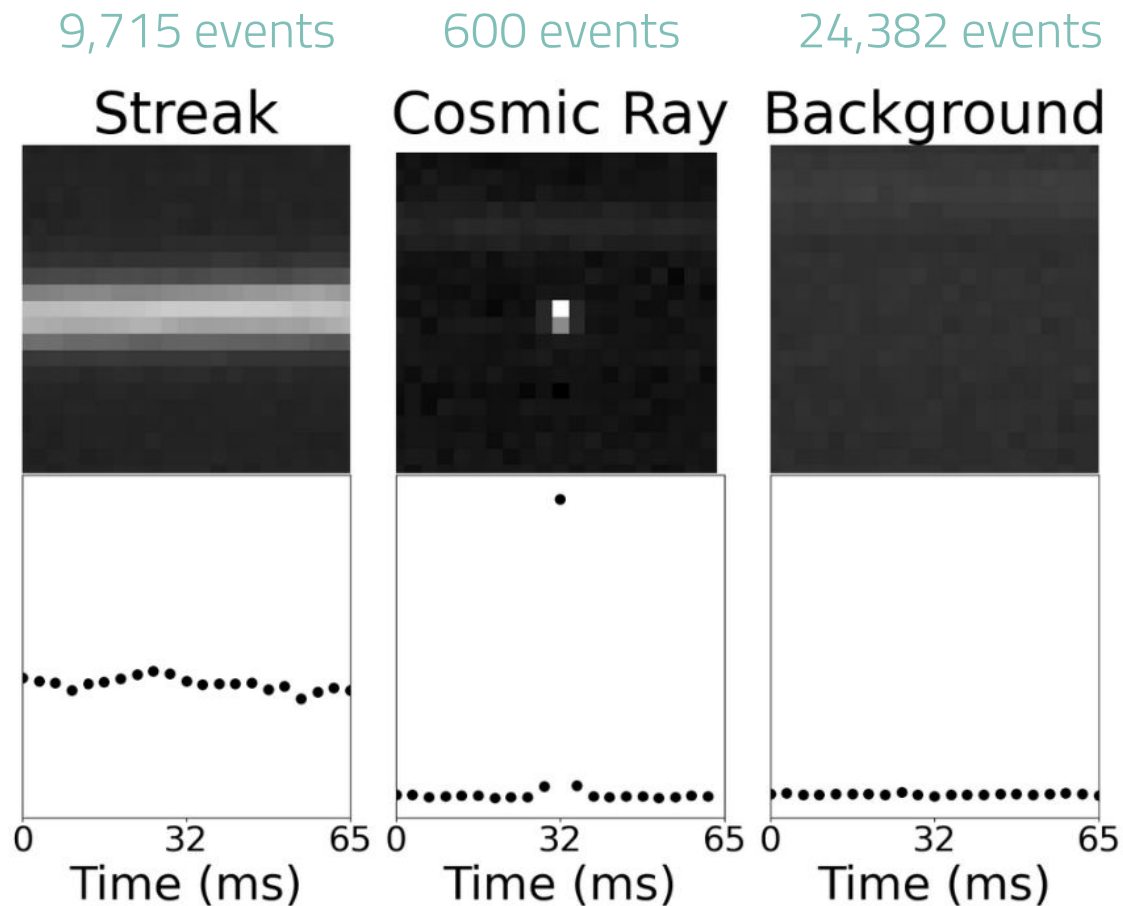


## Streak, cosmic ray, and background training datasets were chosen from data

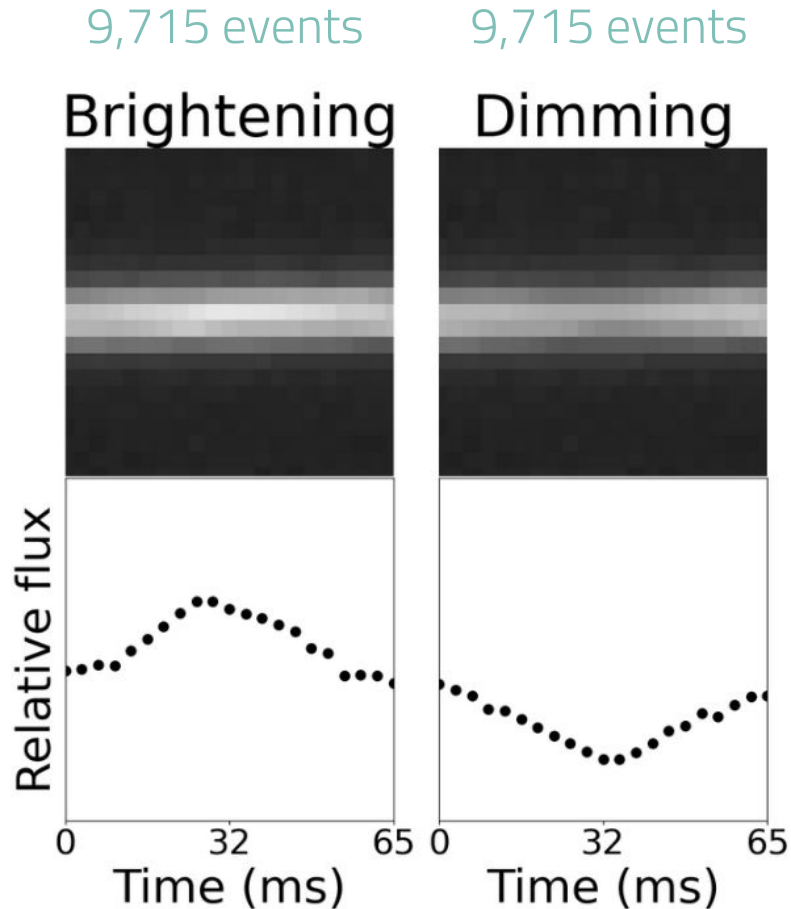
Streaks: One stamp was taken from each of the ~ten brightest streaks per image

Cosmic rays: contaminant of early results

Background: taken from the midpoint between streaks on the spatial axis if the streaks were separated by more than 25 pixels



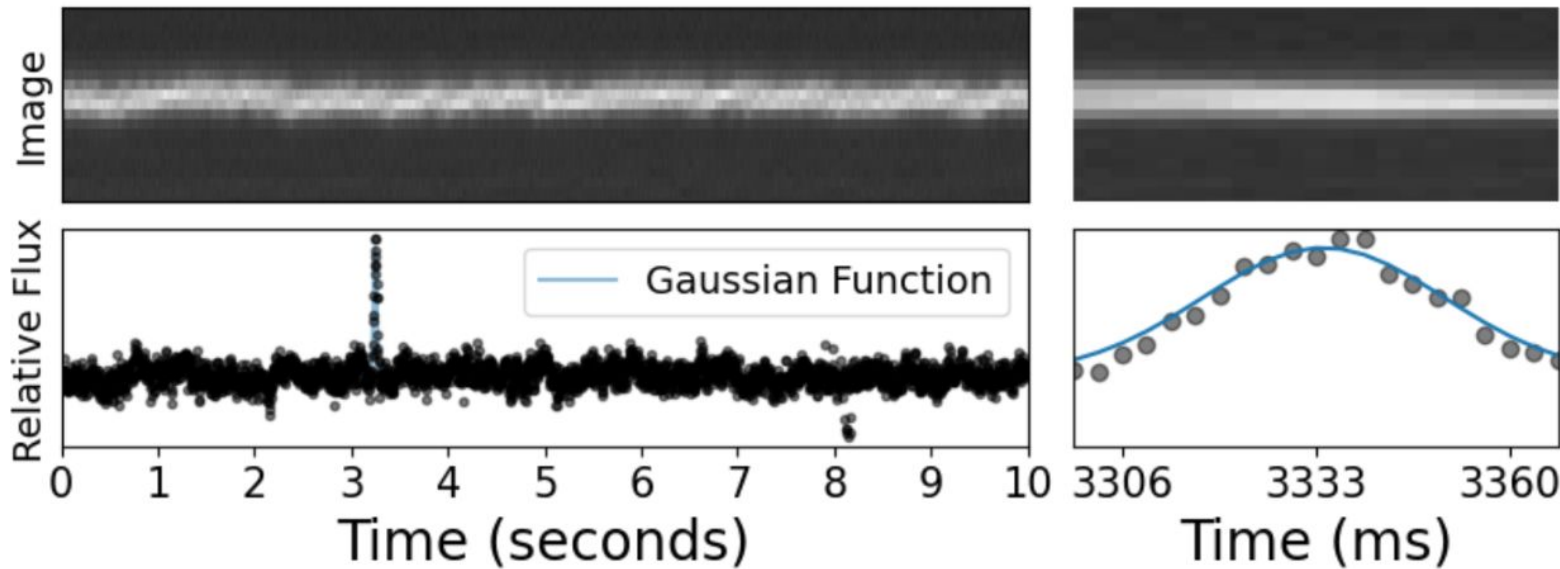
## Brightening and dimming transients were implanted in streaks



$$F_{event} = F \left( (A - 1)e^{-\frac{(y-\mu)^2}{2w^2}} + 1 \right)$$

- A is the amplitude,
- $\mu$  is the event center pixel on the time axis,
- y is the pixel number corresponding to the time axis,
- w is the standard deviation of the Gaussian model, or duration of the event.

# Brightening Training Implantation



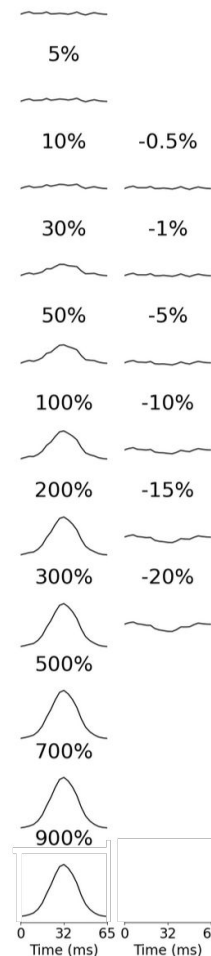
# Building a training set

## Two parameters varied for brightening and dimming events:

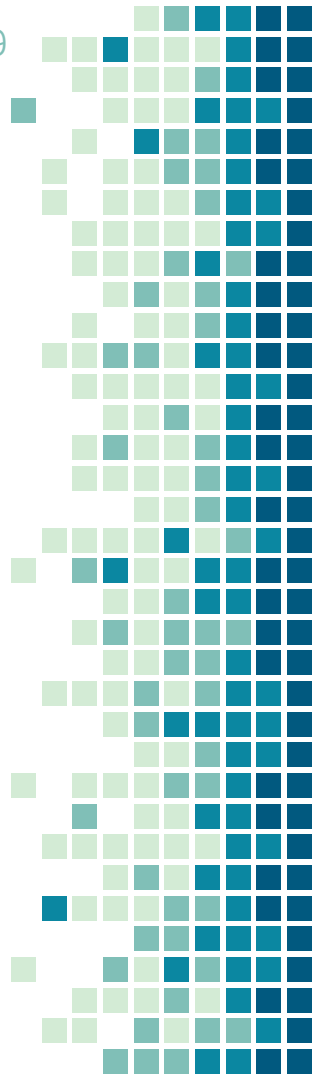
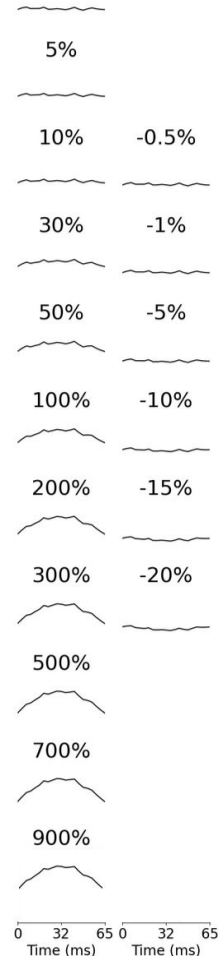
The duration  $w$  varied evenly in the range 3-9 pixels ( $\sim 10$ – $30$  ms)

The amplitude distribution was biased towards lower intensities

1% sigma=3



1% sigma=9

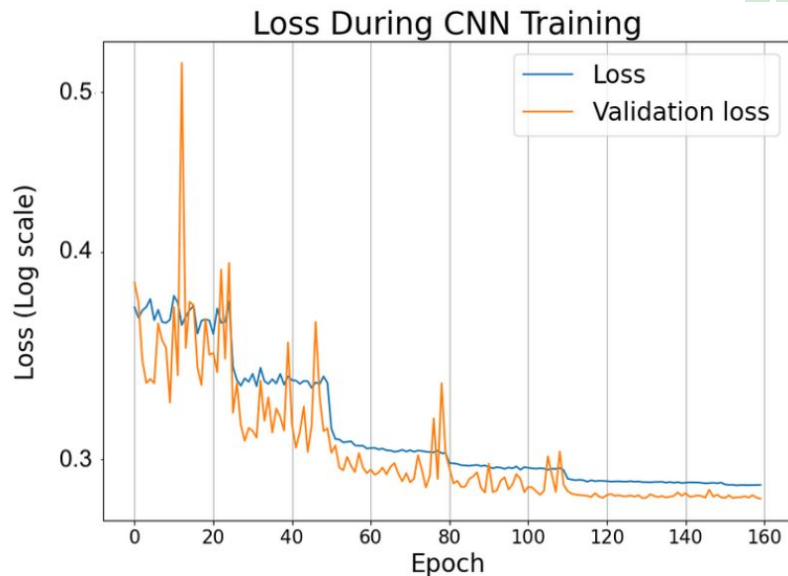


# CNN Training

It happened!

The loss (the function that is minimized during training) is shown over each training epoch.

The loss function used was “categorical cross entropy.”

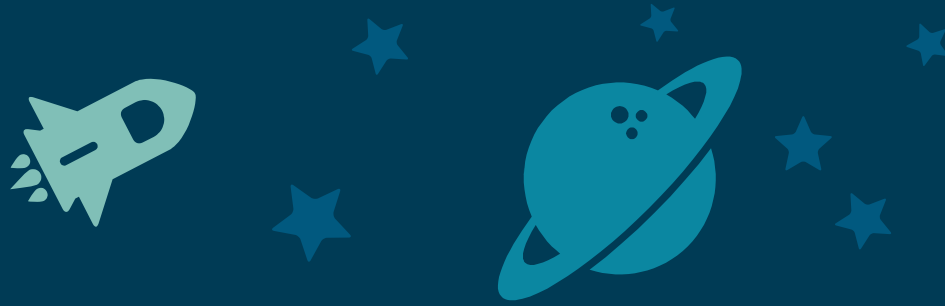


$$L(y, \hat{y}) = - \sum_{i=1}^{N_c} y_i \log(\hat{y}_i)$$

$L(y, \hat{y})$  is the loss,

$y_i$  is the true label for each class  $i$

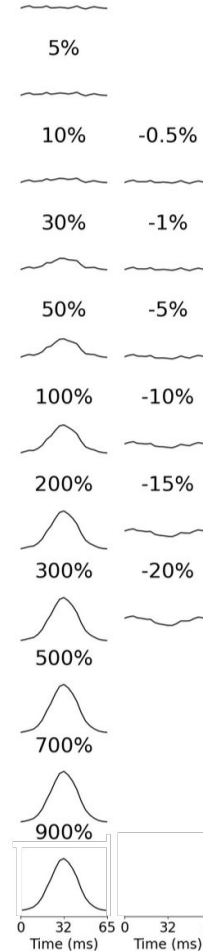
$\hat{y}_i$  is the predicted probability for each class



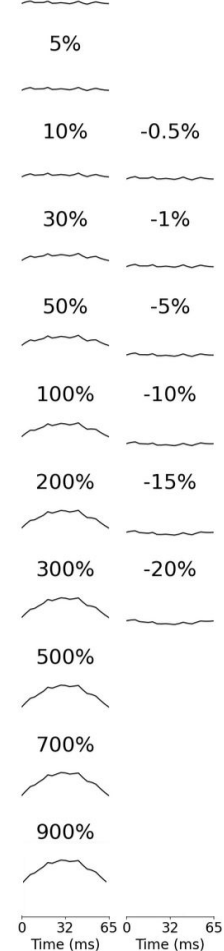
How successful is the CNN at categorizing pixels?

Answer: the success rate depends on the amplitude and duration of the transient

1% sigma=3



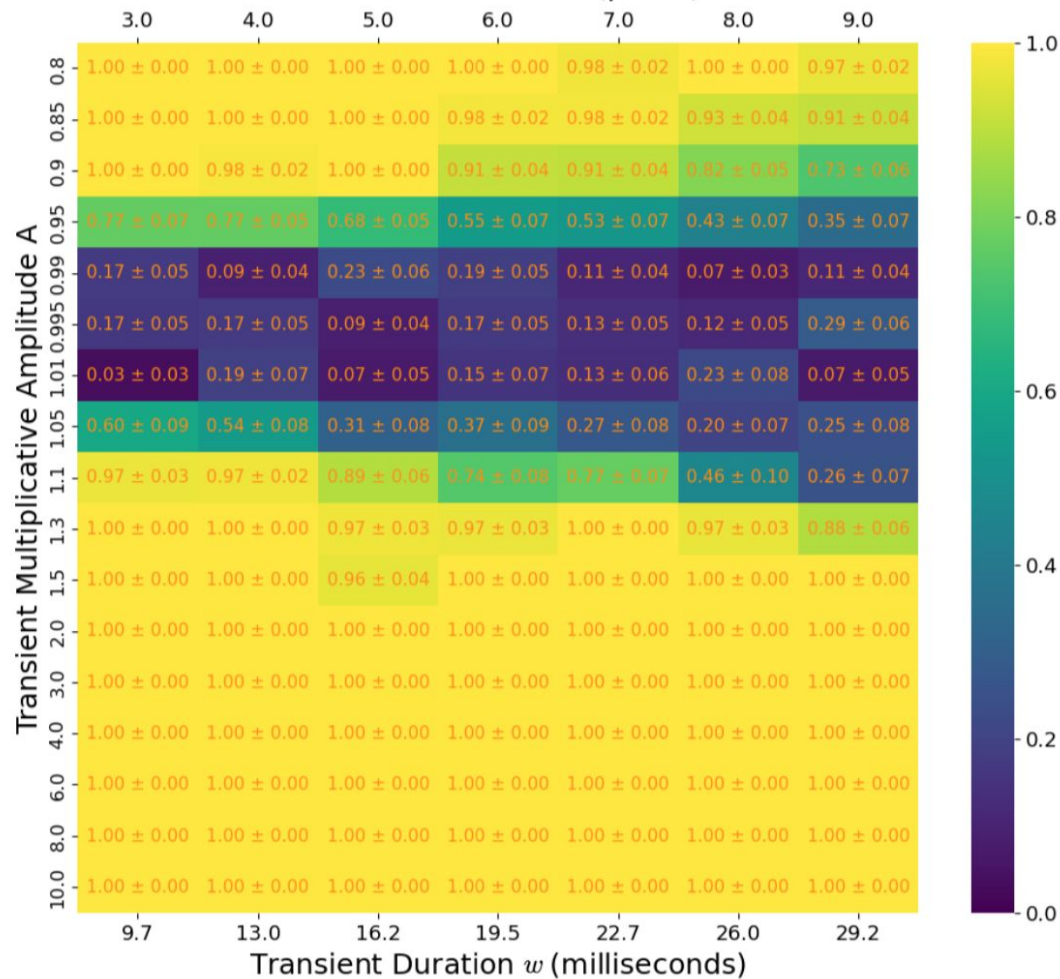
1% sigma=9



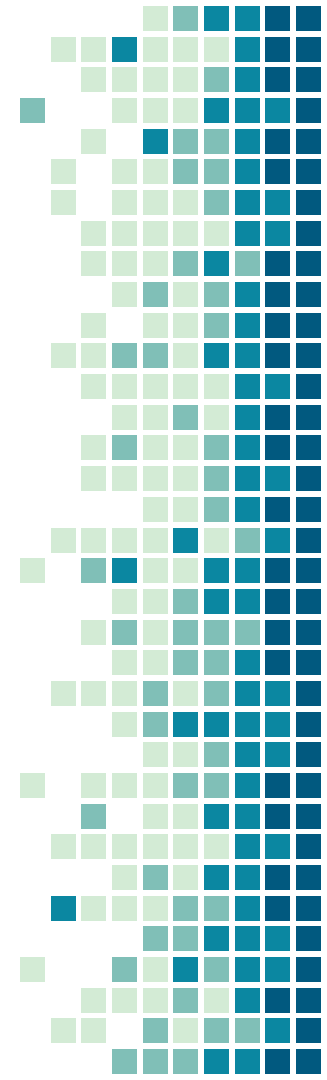


# Transient Detection Efficiency Heatmap

Transient Duration  $w$  (pixels)

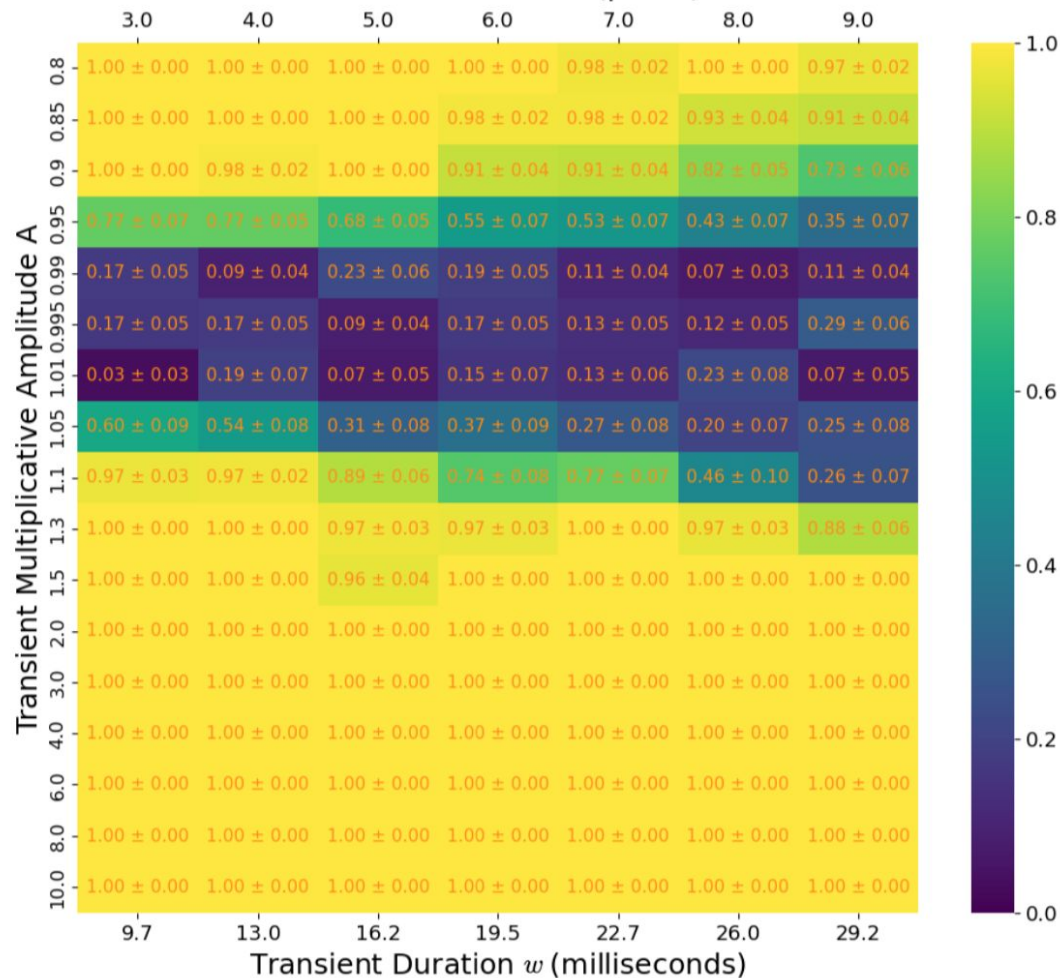


$$\frac{N_{\text{retrieved}}}{N_{\text{total}}}$$



# Transient Detection Efficiency Heatmap

Transient Duration  $w$  (pixels)



Very successful  
at  $A < 0.9$

Failure as we  
approach  $A = 1$   
(no amplitude  
change)

Very successful  
at  $A > 1.1$



How can we use the CNN's  
pixelwise categorizations to  
categorize transient events?

# Postprocessing steps

1. Aggregate pixelwise predictions into potential transients
2. Reject recognizable artifacts and contaminants
3. Extract light curves
4. Quantify noise and apply cutoffs
5. Extract transient parameters

CNN output by the numbers:

- 6,399,234 pixels classified as belonging to brightening transients,
- 4,398,521 pixels classified as belonging to dimming transients

### 3. Extract light curves

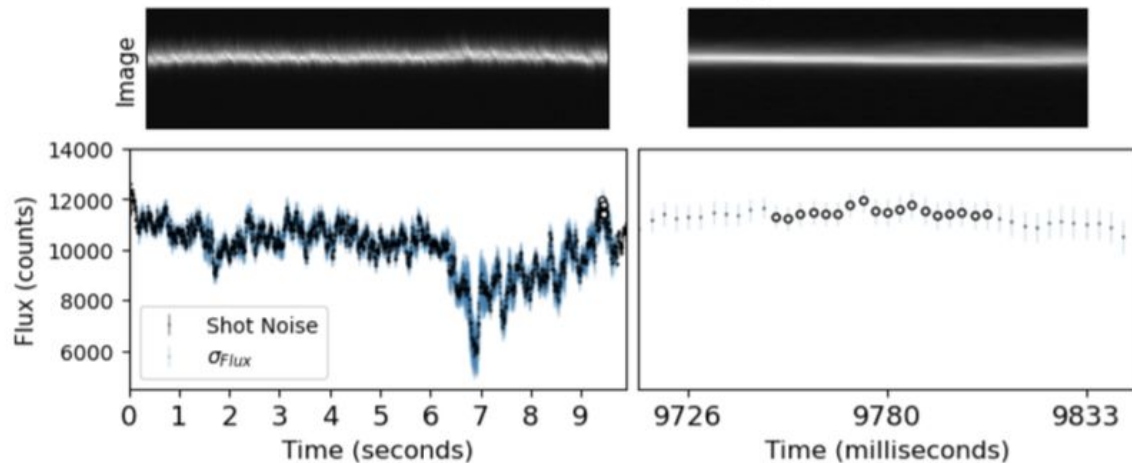
Postprocessing up to this point leads to:

67,796 brightening transients,

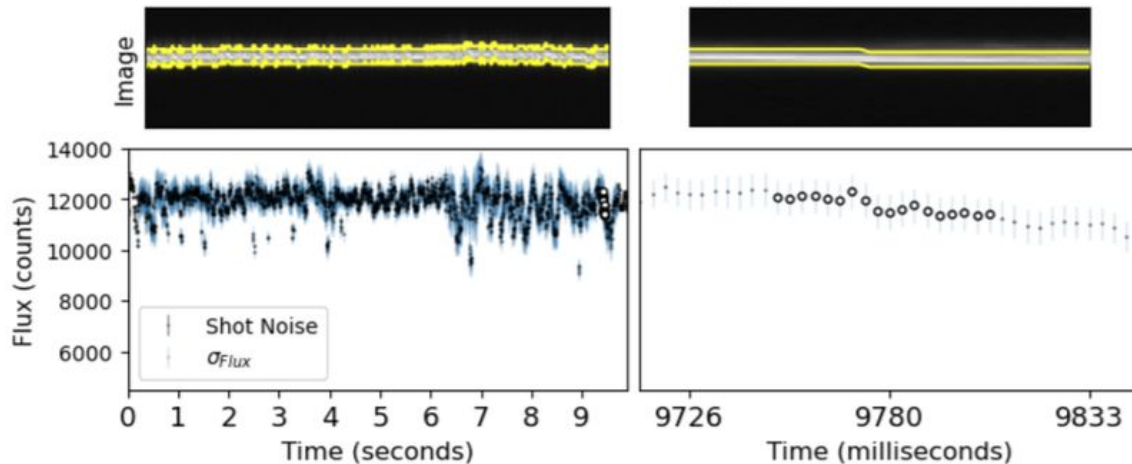
238,259 dimming transients

We let the center of the aperture be the brightest pixel for each time step, which we call “Tracking.”

Before Tracking



With Tracking



## 4. Quantify noise and apply cutoffs

### Shot noise

$$\epsilon_{Poisson} = \sqrt{\frac{F}{G} + (N_{read})^2}$$

F is the pixel value in counts

G is the gain, which for these observations is set to  $G = 6.2$

$N_{read}$  is the read noise, = 8.5 for our data

### Standard deviation of data

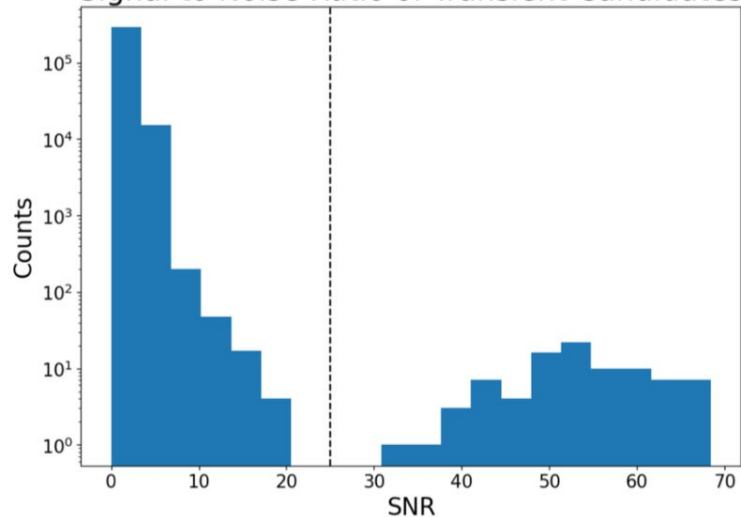
Calculated over 100 pixels on either side of the transient, excluding the 20 pixels (size of the stamp) centered on the transient

Leads to our SNR definition:

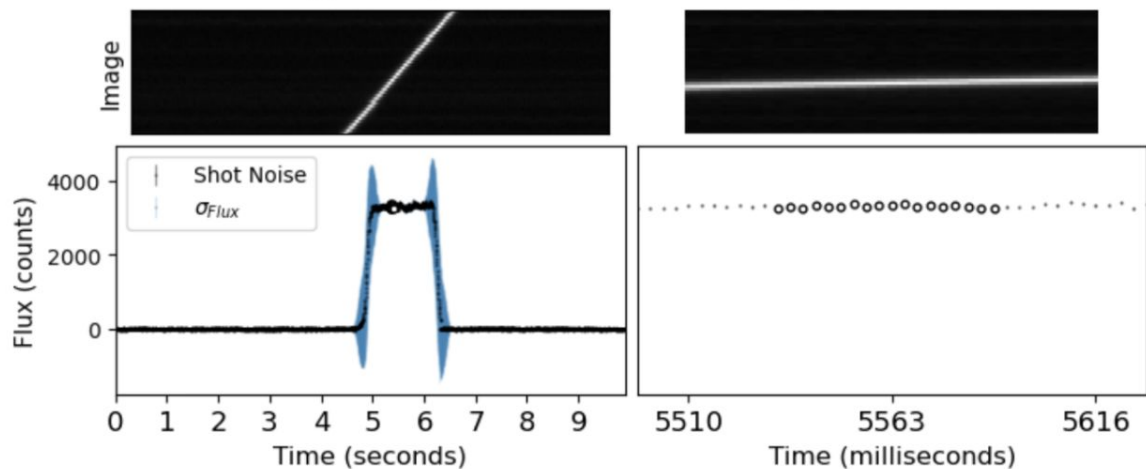
$$SNR = \frac{\max |F_T| - \langle F_{streak} \rangle}{\sigma_{Flux}}$$

## 4. Quantify noise and apply cutoffs

Signal to Noise Ratio of Transient Candidates



Moving Object Detection, SNR 65



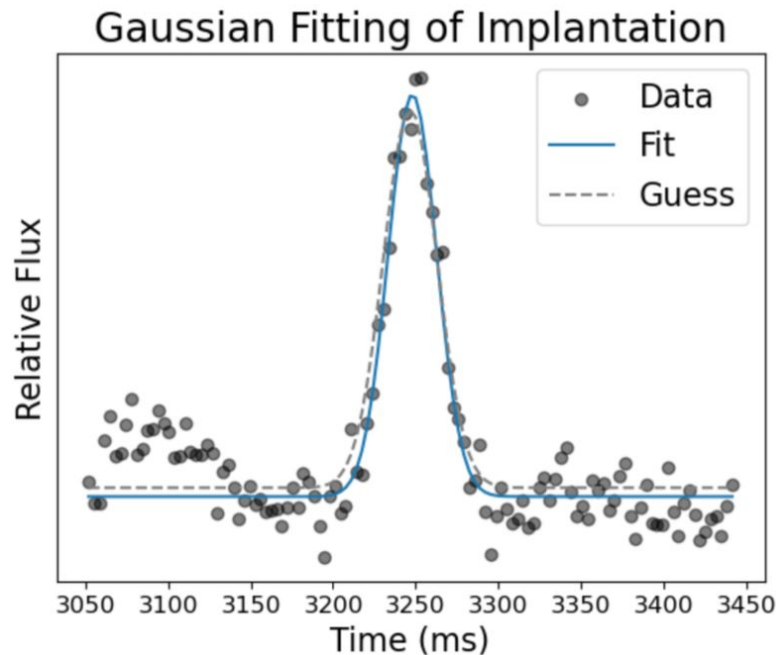
**SNR > 25 indicates a moving object**

## 5. Extract transient parameters

### Gaussian Template Fitting

$$F_{\text{transient},i} = F_0 \left( (A - 1) * e^{\frac{-(y_i - \mu)^2}{2w^2}} + 1 \right)$$

- A is the amplitude,
- $\mu$  is the event center pixel on the time axis,
- y is the pixel number corresponding to the time axis,
- w is the standard deviation of the Gaussian model, or duration of the event





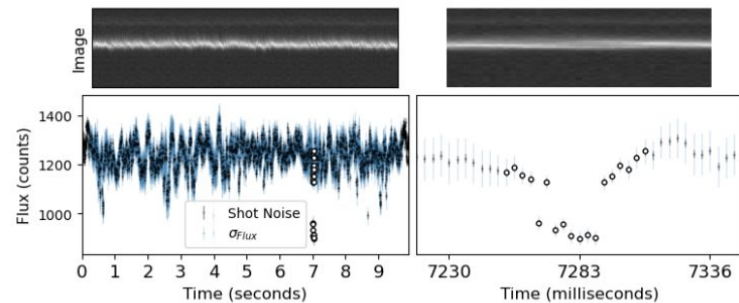


What transient candidates  
have I found?

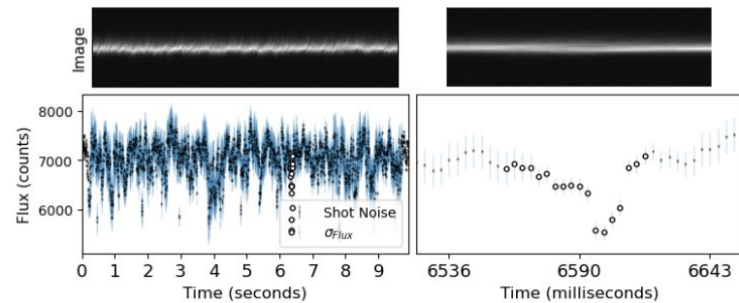
# Dimming Transient Candidates

Candidate ID	89360	287440	300741
Field ID	449	449	449
Observation Date	10/20/2022	10/20/2022	10/20/2022
Filter	$r$	$r$	$r$
CCD ID and Quadrant	14; 1	13; 4	09; 2
Sobel Ratio	12.1	9.58	9.32
SNR	11.5	9.14	10.2
$\mu$ (ms)	7089.99	6418.83	4476.88
$w$ (ms)	10.18	22.96	22.42
Minimum Flux $A$ (counts)	0.718	0.904	0.753
Baseline Flux $F_0$ (counts)	1234.5	7151.1	1446.4

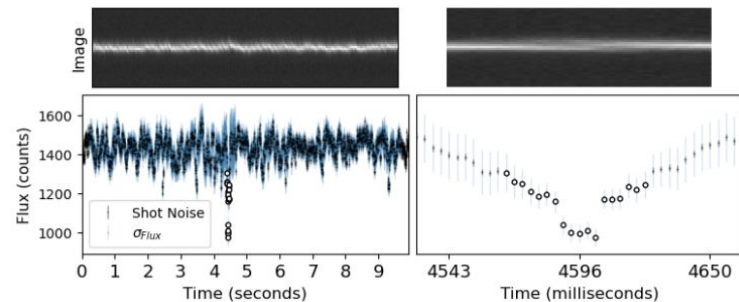
Possible Transient # 89360



Possible Transient # 287440



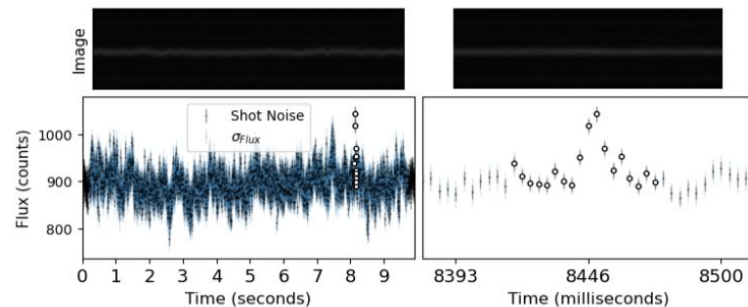
Possible Transient # 300741



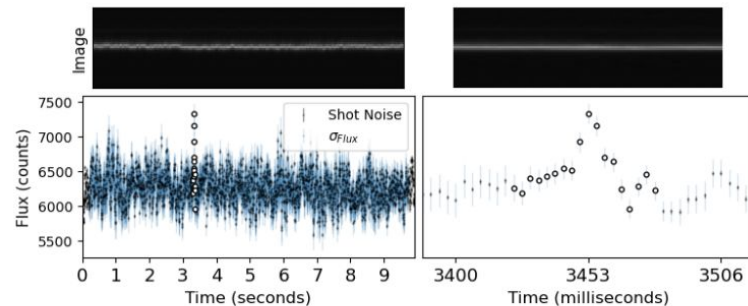
# Brightening Transient Candidates

Candidate ID	107085	124163	145388
Field ID	686	640	640
Observation Date	10/20/2022	10/20/2022	10/20/2022
Filter	<i>g</i>	<i>i</i>	<i>g</i>
CCD ID and quadrant	16; 2	09; 4	06; 3
Sobel Ratio	5.36	10.9	5.15
SNR	7.11	7.38	7.18
$\mu$ (ms)	8229.57	3363.63	6522.56
$w$ (ms)	3.72	7.10	2.13
Peak Flux (counts) $A$	1.155	1.124	1.073
Baseline Flux $F_0$ (counts)	903.8	6232.8	1826.3

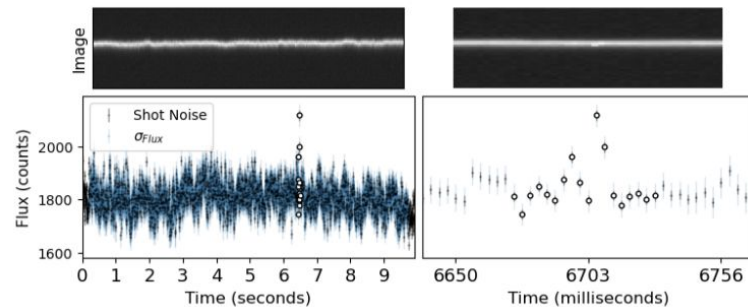
Possible Transient # 107085



Possible Transient # 124163



Possible Transient # 145388



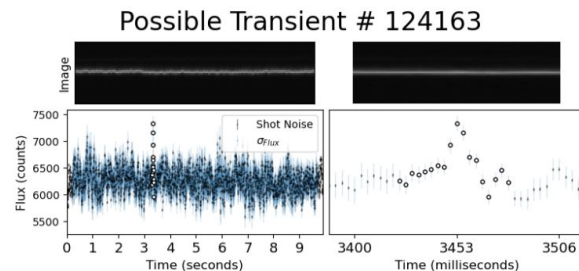
# CONCLUSION + TAKEAWAYS

## Fast optical transients:

- Astronomers have barely explored what in the sky varies in less than a day
- Transients are often extreme, high-energy phenomena that test fundamental physics
- Surveying wide areas of sky to find subsecond transients is possible using continuous-readout mode imaging

## My analysis process:

- I built a pipeline that retrieves subsecond astrophysical transient events in continuous-readout mode data
- Retrieved several candidate events for further study

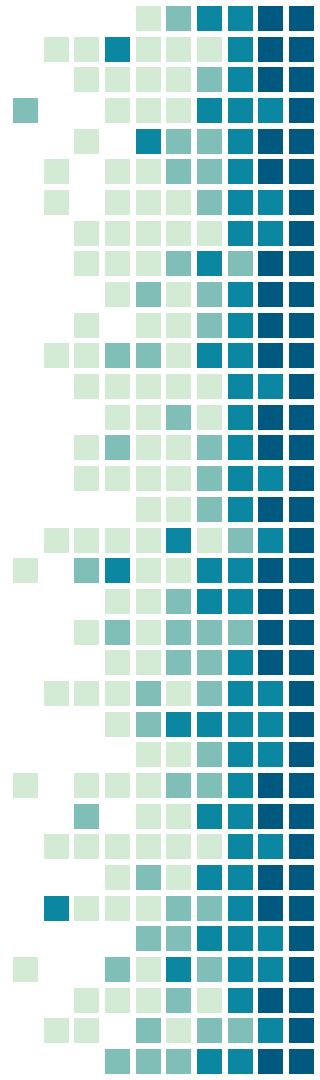


# Future work

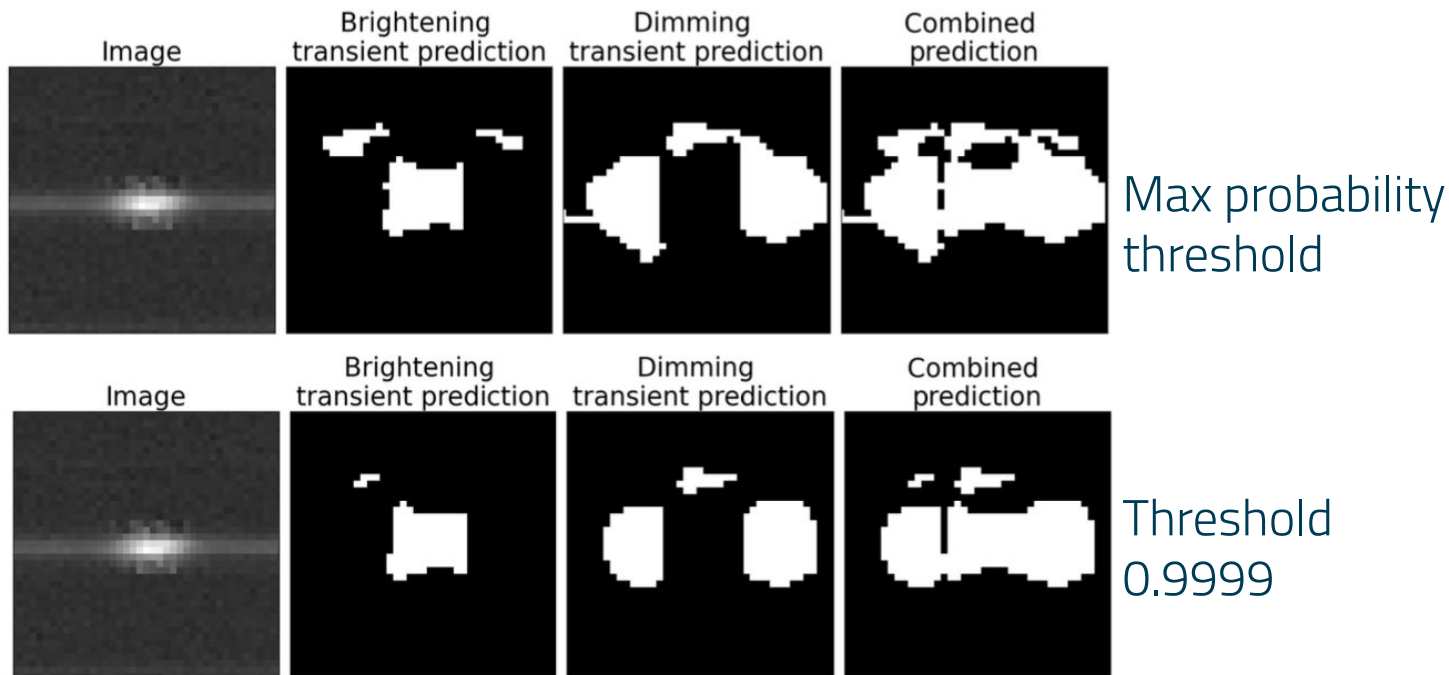
Replace convolutional neural network with transformer neural network

Transformer advantages:

- Type of NN suited to sequential data (like a time series)
- Can view whole streak, not just 20x20 pixel square
- Can understand repetitive patterns of variability
- Can view the relative behavior of multiple streaks to rule out some artifacts



# 1. Aggregate pixelwise predictions into potential transients



Results in:

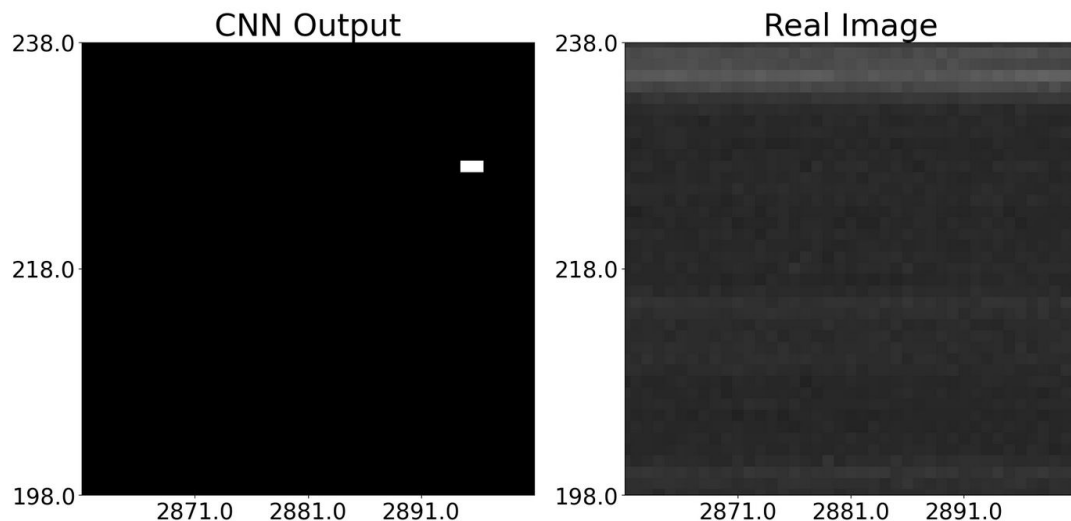
605,259  
brightening  
transients,

520,787  
dimming  
transients,

10,530  
cosmic rays.

## 2. Reject recognizable artifacts and contaminants

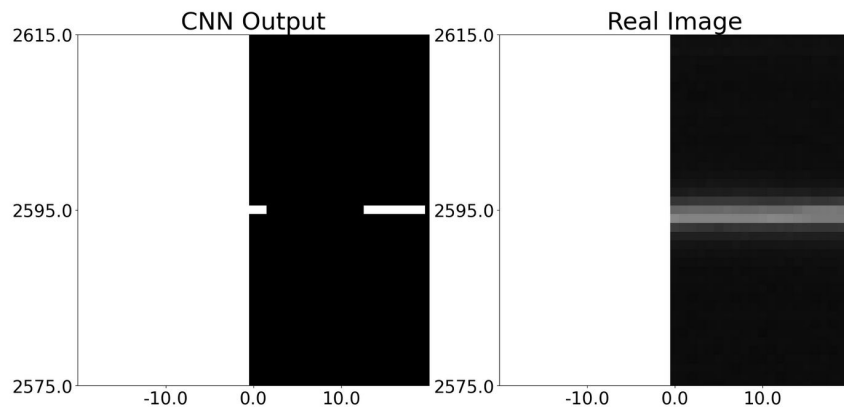
1. We remove transient candidates that are less than 5 pixels  
these are likely cosmic rays or other artifacts of the image or of the CNN



## 2. Reject recognizable artifacts and contaminants

1. We remove transient candidates that are less than 5 pixels
2. We remove transient candidates that are within 15 pixels of the edges of the image

the CNN was not trained to interpret the edge of the image

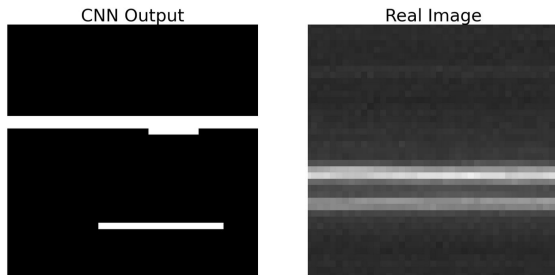




## 2. Reject recognizable artifacts and contaminants

1. We remove transient candidates that are less than 5 pixels
2. We remove transient candidates that are within 15 pixels of the edges of the image
3. We remove anything that doesn't have a pixel brightness of at least 300 counts in the center  $8 \times 8$  square of the postage stamp

real transient events come from a streak (star/galaxy)



Results in:

69,090

brightening  
transients,

238,580

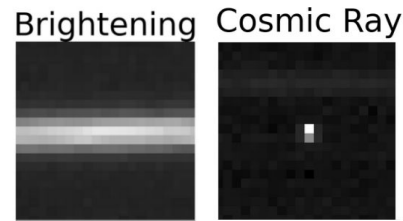
dimming  
transients,

10,530

cosmic rays.

## 2. Reject recognizable artifacts and contaminants

- Real transients expected to have smooth edges along the time axis
- Cosmic rays have sharp edges
- Ratio of edge sharpness calculated with Sobel–Feldman edge detection filter



Sobel+ 2022  
Virtanen+ 2020

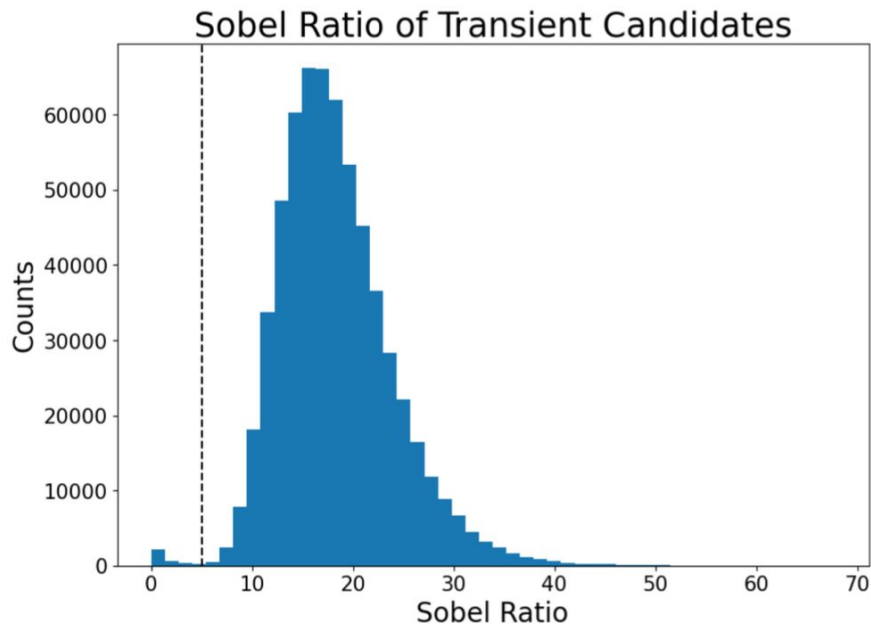


Sobel  
filter  
in x

Sobel  
filter  
in y



## 2. Reject recognizable artifacts and contaminants



Transient candidates with sobel ratio <5 removed

Results in:

67,796

brightening  
transients,

238,259

dimming  
transients,

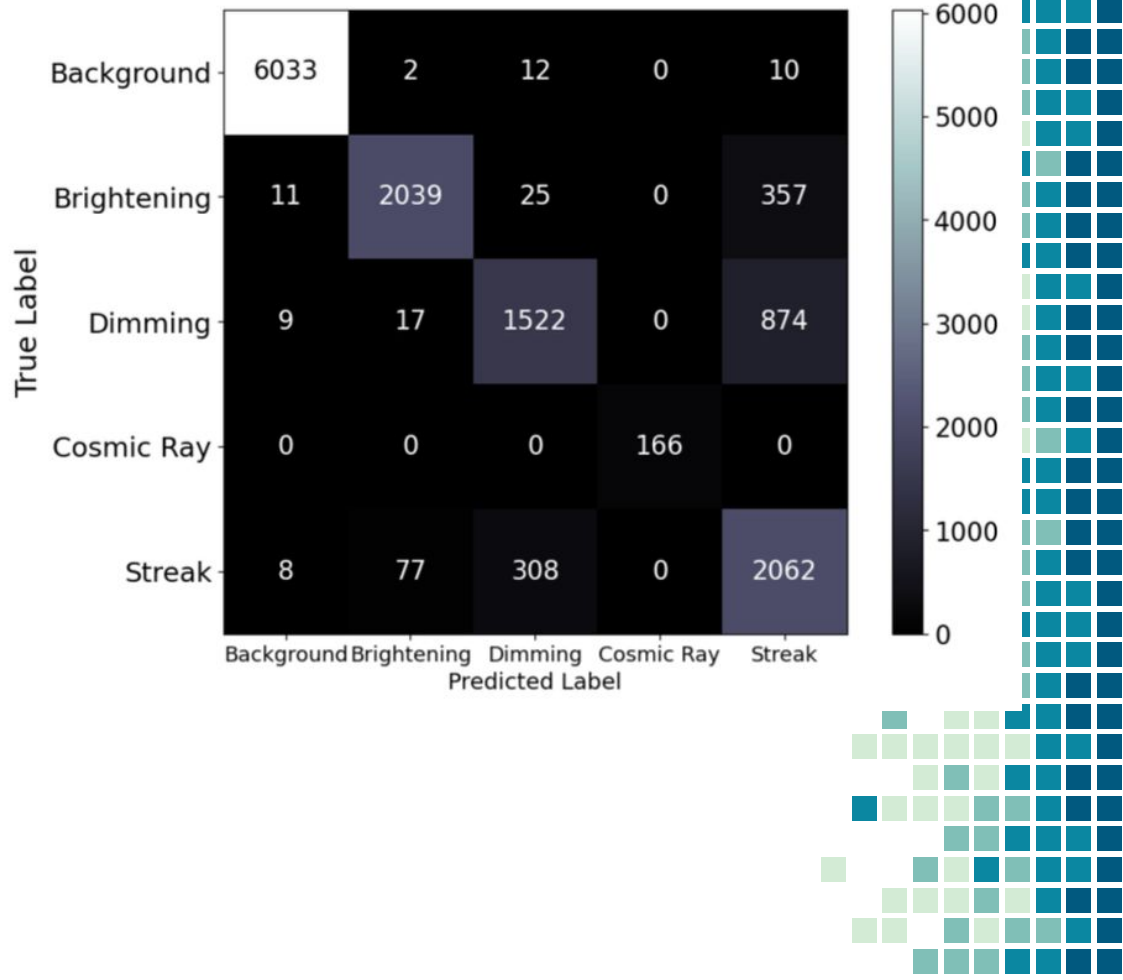
13,338

cosmic rays.

# Confusion Matrix

Very successful at:

- Background



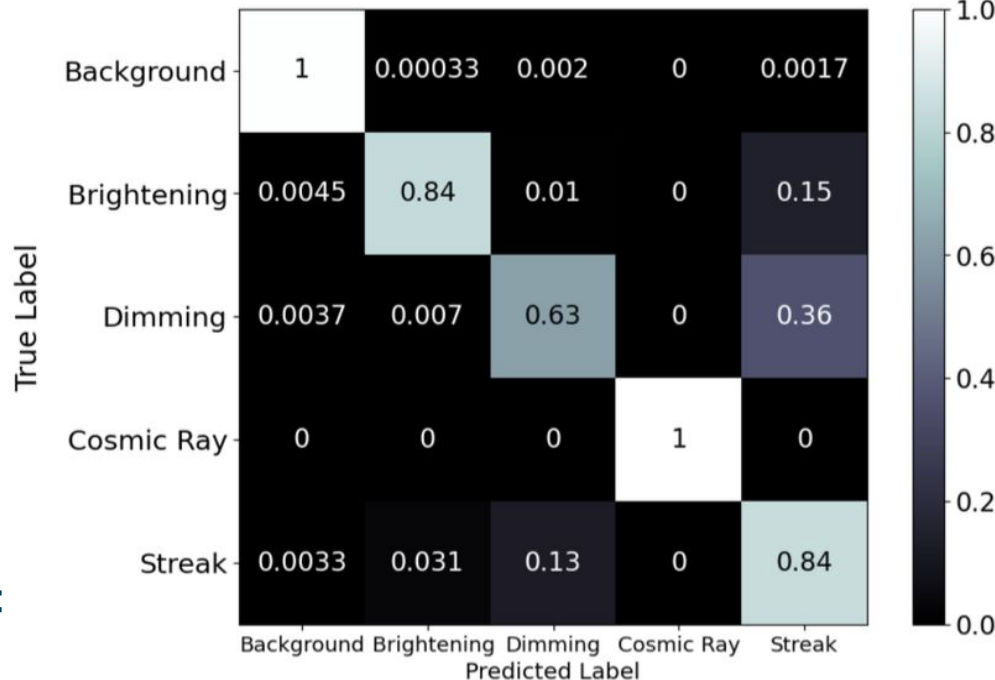
# Confusion Matrix

Very successful at:

- Background
- Cosmic ray

Biggest source of confusion:

- Dimming transients
  - Often confused for streaks or brightening transients



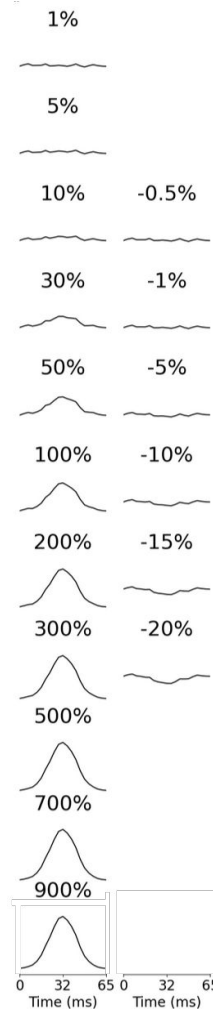
# Confusion Matrix

Very successful at:

- Background
- Cosmic ray

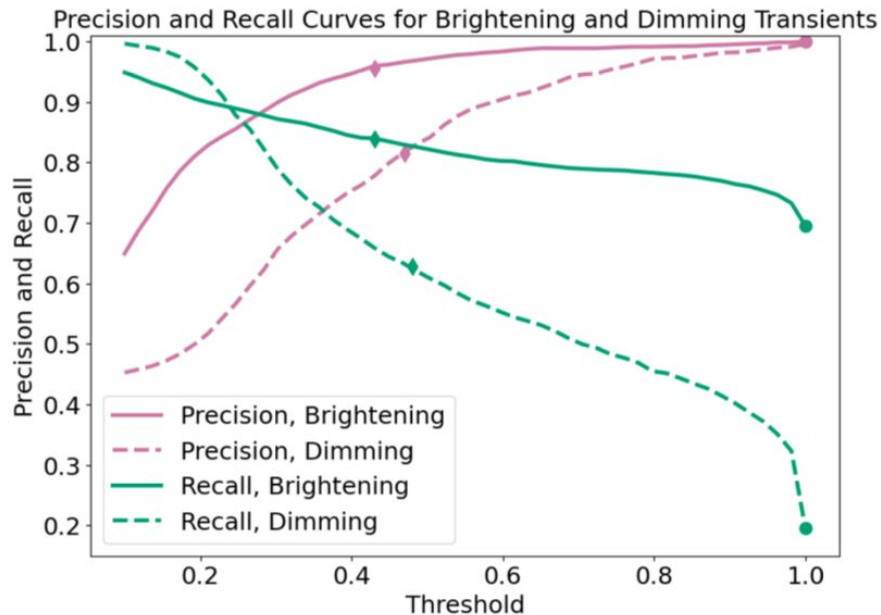
Biggest source of confusion:

- Dimming transients
  - Often confused for streaks or brightening transients



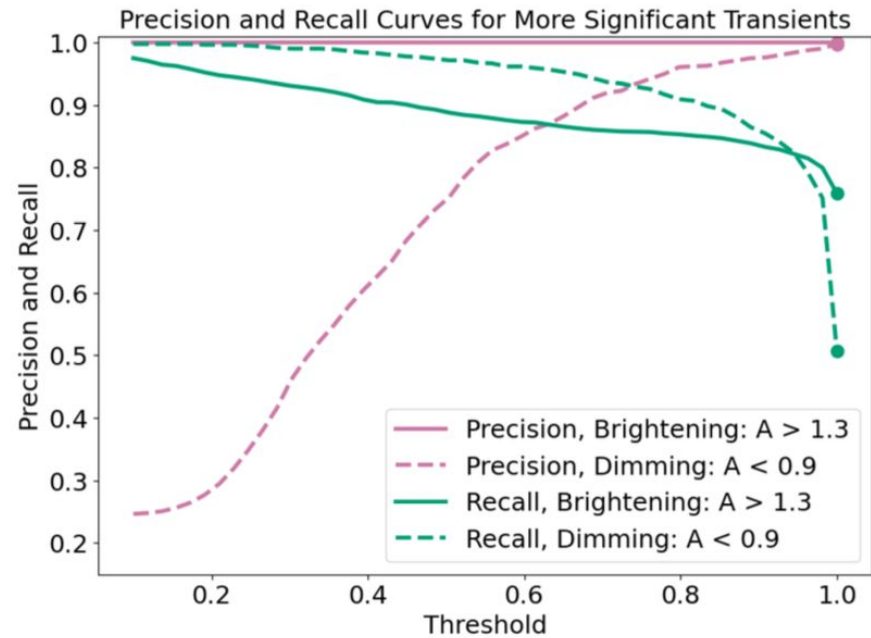
**Recall some brightening/dimming transients that we tested on are very subtle...**

**Let's investigate success rate per A**



(a)  $C = \vec{C}[\argmax(\vec{P})]$

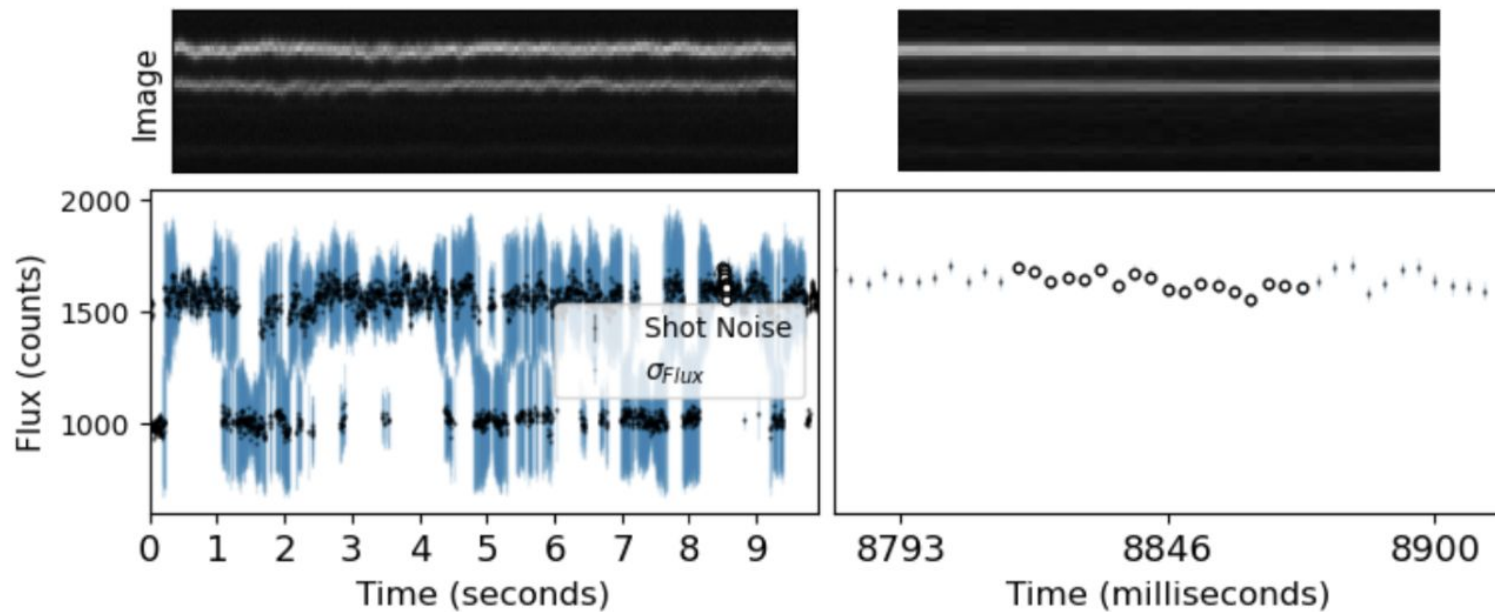
$C = \vec{C}[\argmax(\vec{P})]$	Precision	Recall
Brightening	0.955	0.838
Dimming	0.815	0.628



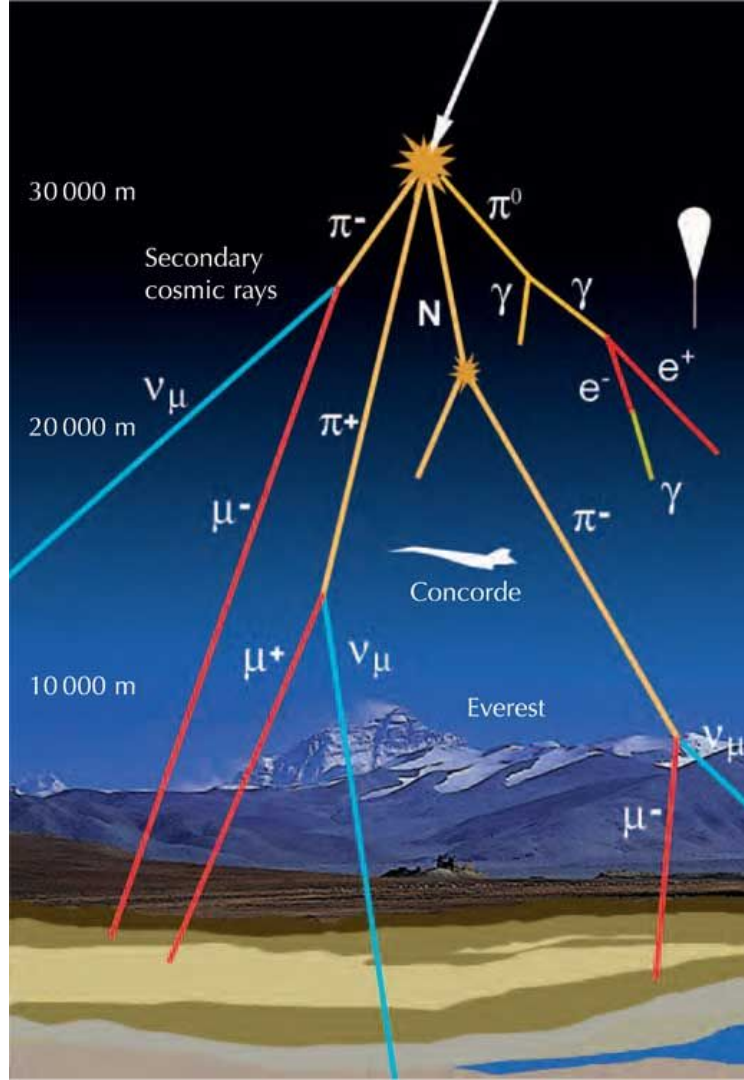
(b)  $C = T \iff P_T \geq 0.9999$

$C = T \iff P_T \geq 0.9999$	Precision	Recall
Brightening	1.000	0.695
Dimming	0.996	0.196

# Double Streak Detection







<https://physic.sopenlab.org/2016/01/10/cosmic-muons-decay/>

