Finding exoplanets with TESS & AI

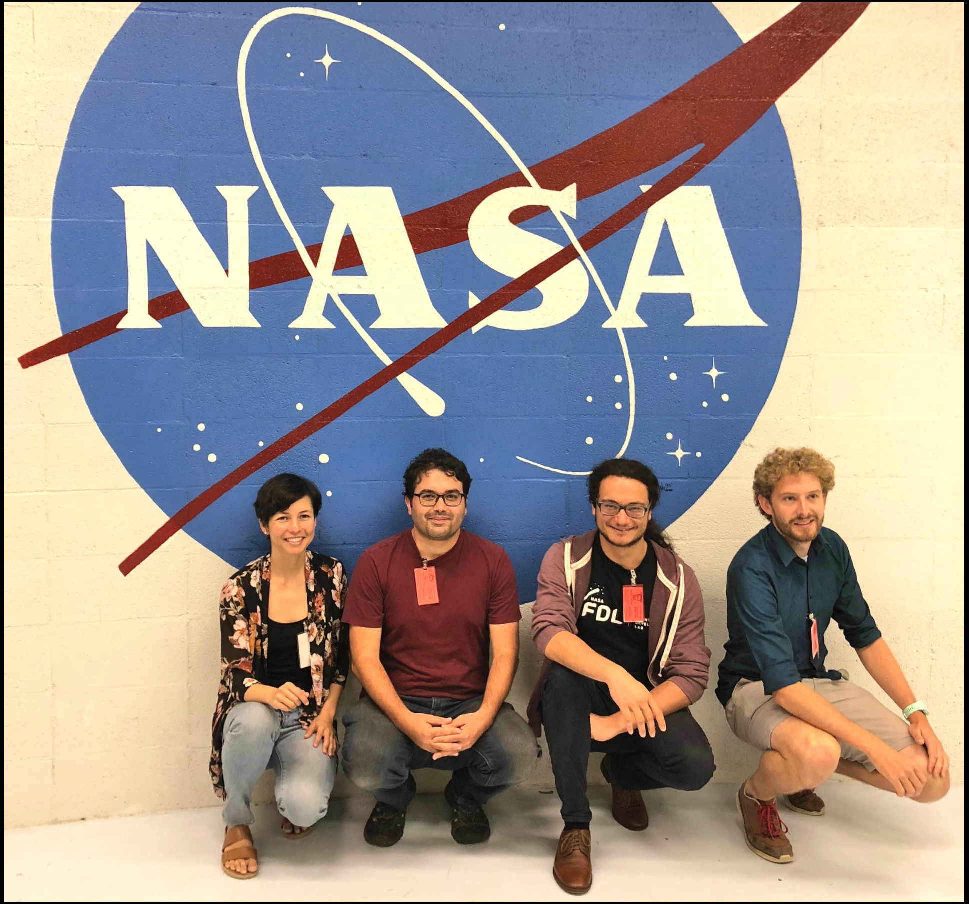
EXOPLANETS

Google Cloud kx

Megan Ansdell, Yani Ioannou, **Hugh Osborn**, Michele Sasdelli,

+ Jeff Smith, Jon Jenkins, Doug Caldwell, Adam Lesnikowski, Chedy Raissi, Massimo Mascaro

The Team



Megan Ansdell, Yani Ioannou, Michele Sasdelli, Hugh Osborn

Frontier Development Lab

Space Science Researchers

Machine Learning Researchers

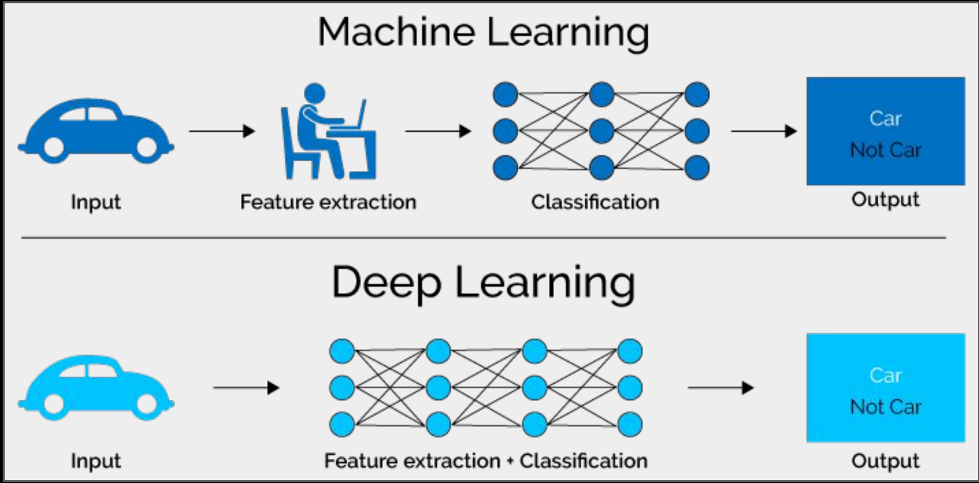
Silicon Valley Partners

- 8 week research accelerator hosted at NASA Ames & SETI
- 9 projects across 5 areas proposed by lead mentors

Radical Solutions to problems in Space Science

Deep Learning

- **Excellent at classification problems when:**
  - Lots (N> 10 000s) of labelled data
  - Signal is complex to model (not True for "planet" but true for non-planet!)
- **Once trained, a deep learning algorithm is:**
  - Far faster than classical at performing classification
- **But:**
  - Large computing infrastructure to train
  - Must set aside much of the data as a training set

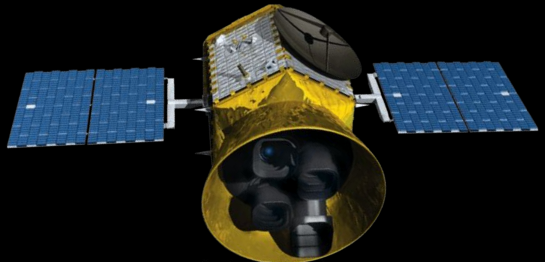


Deep Convolutional Neural Networks

- **Machine Learning (ML):**
  models learn features from data
- **Deep Learning:**
  layers build increasingly complex features
- **Neural Network (NN):**
  model learns weights of nodes
- **Convolutional Neural Network (CNN):**
  exploits spatial structure in data
- **Binary Classification:**
  final layer outputs single number from 0-1

Movie credit: Denis Dmitriev

The Data - TESS

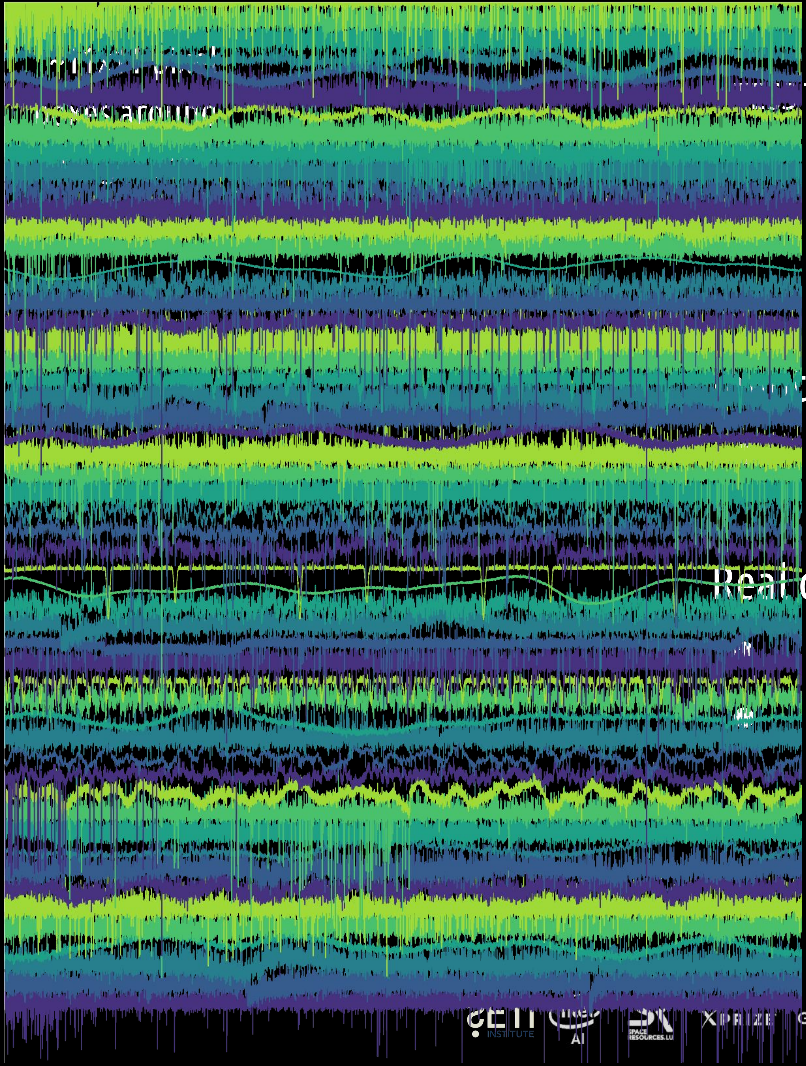


TESS "Data" (TSOP-301 simulations)

Target Pixel Files (simulated planets)

16k stars per sector

2min cadence



TPFs

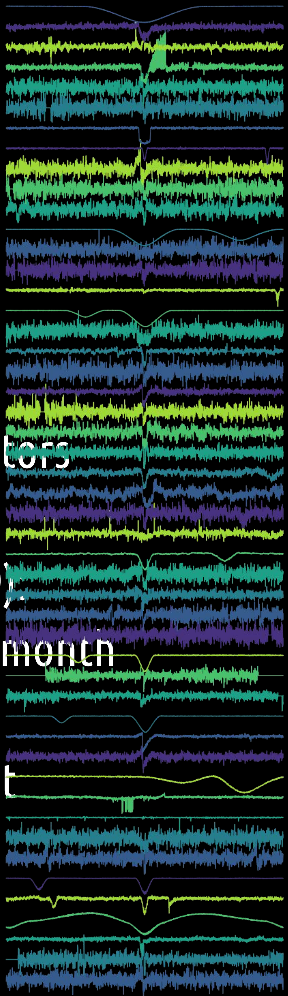
t data:

3 simulated sectors

Real data (from 2019):

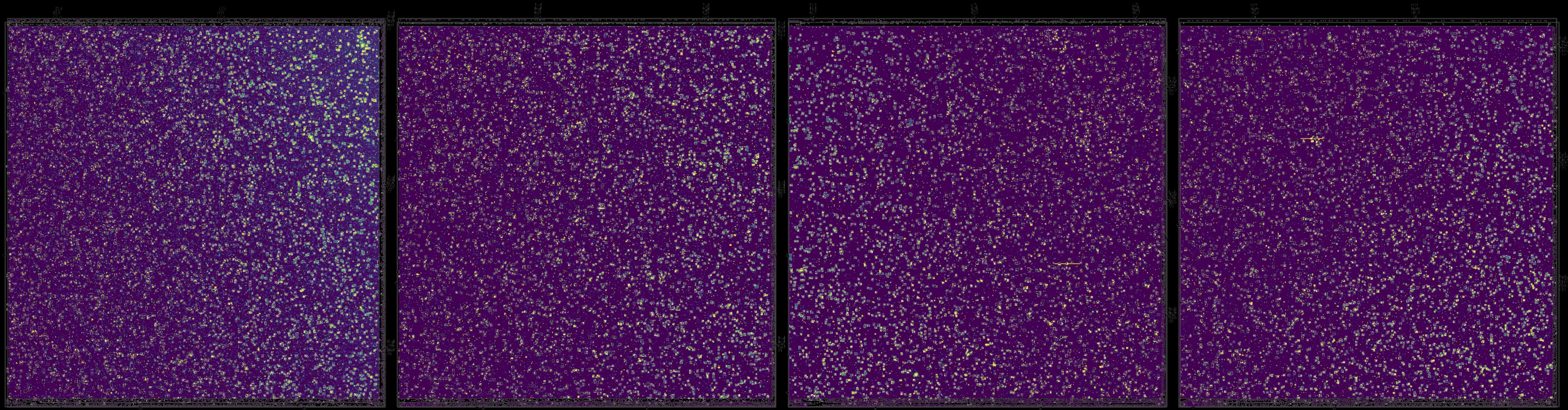
One sector per month

Require rapid, accurate, planet identification



FDL

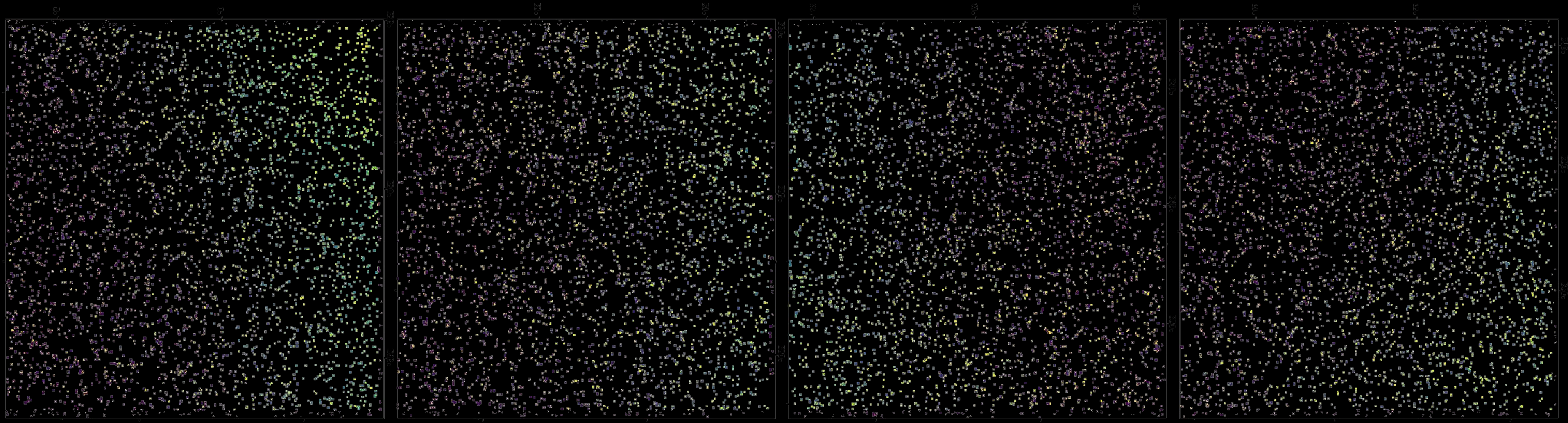
The Data - TESS



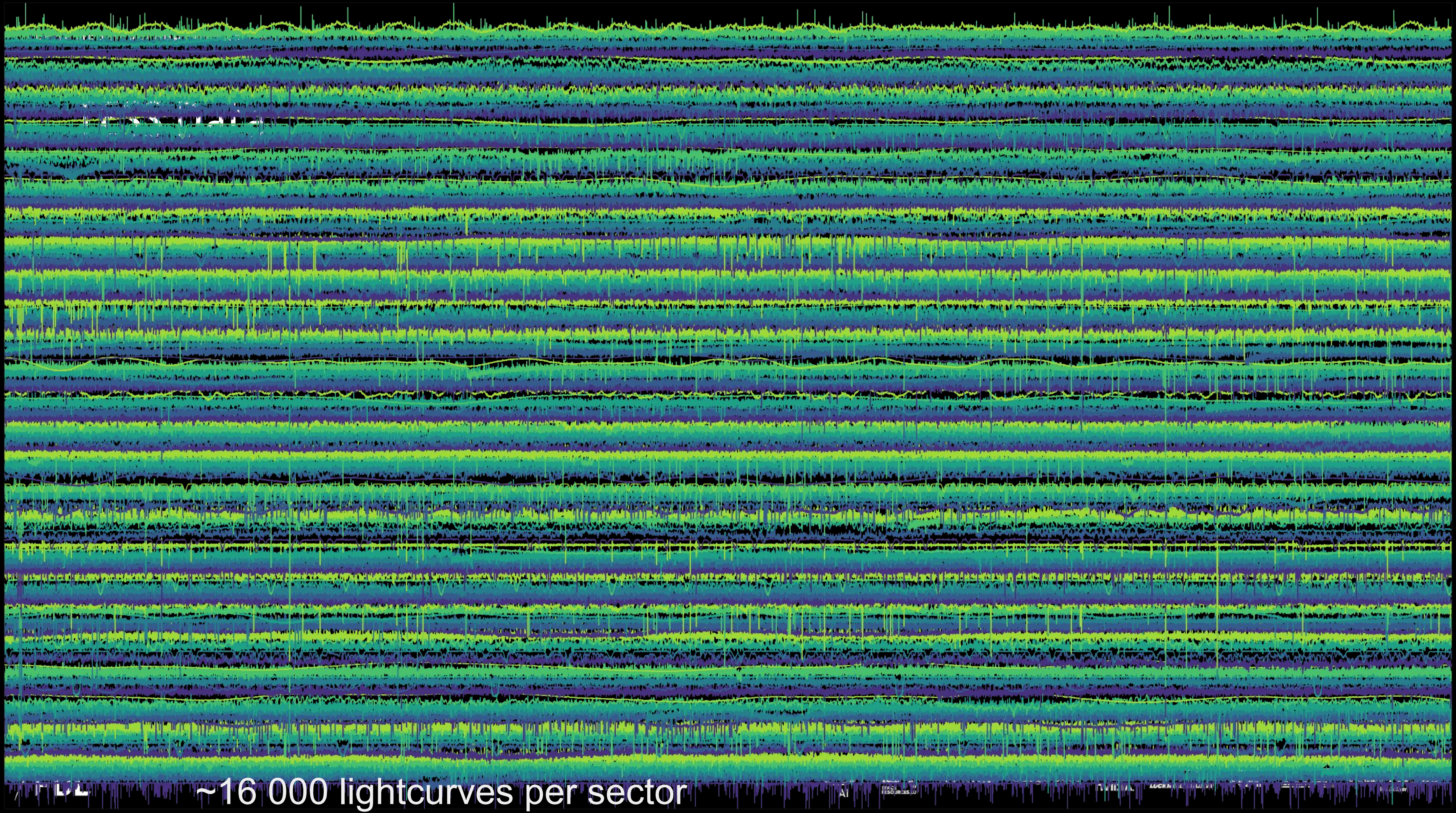
Per month: 4 CCDs ~16 000 target stars 21 000 images

Our dataset: TSOP-301. 4 simulated sectors

TESS - the data bottleneck

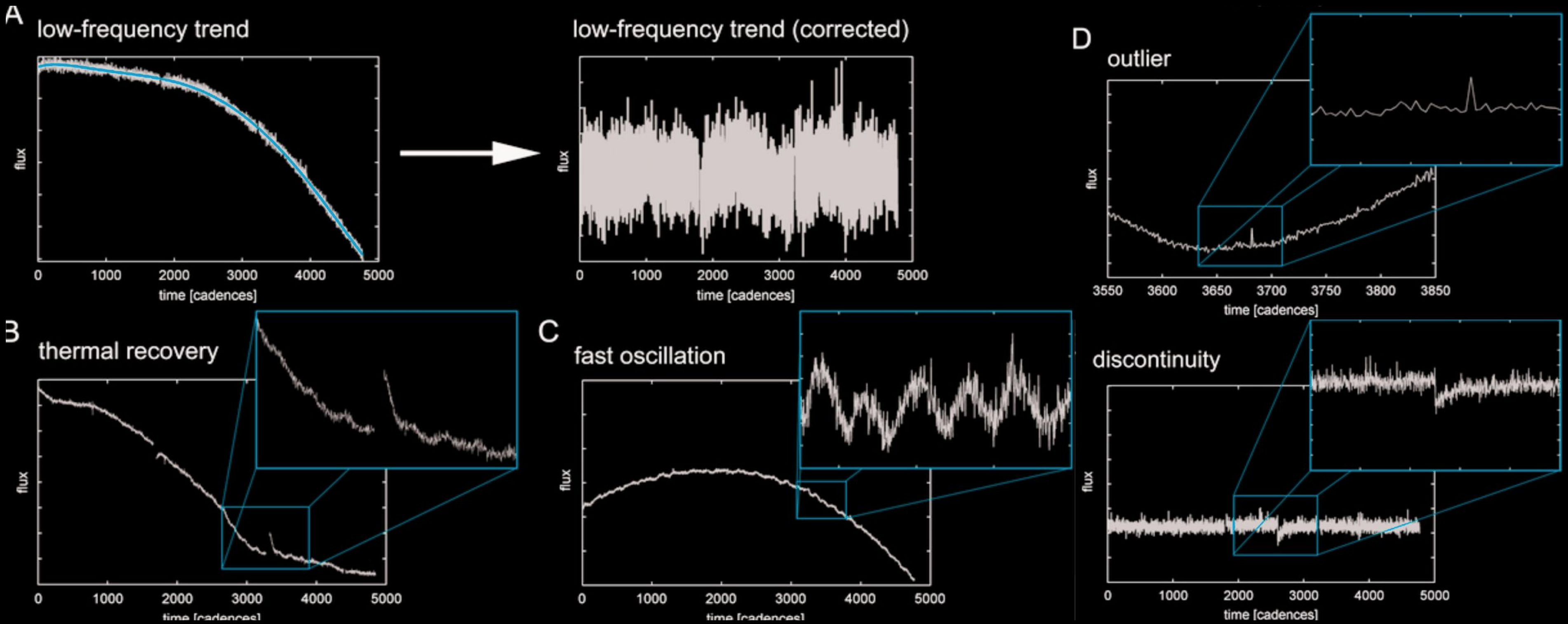


4 simulated sectors ~16 000 stars per month ~4 000 hours of video

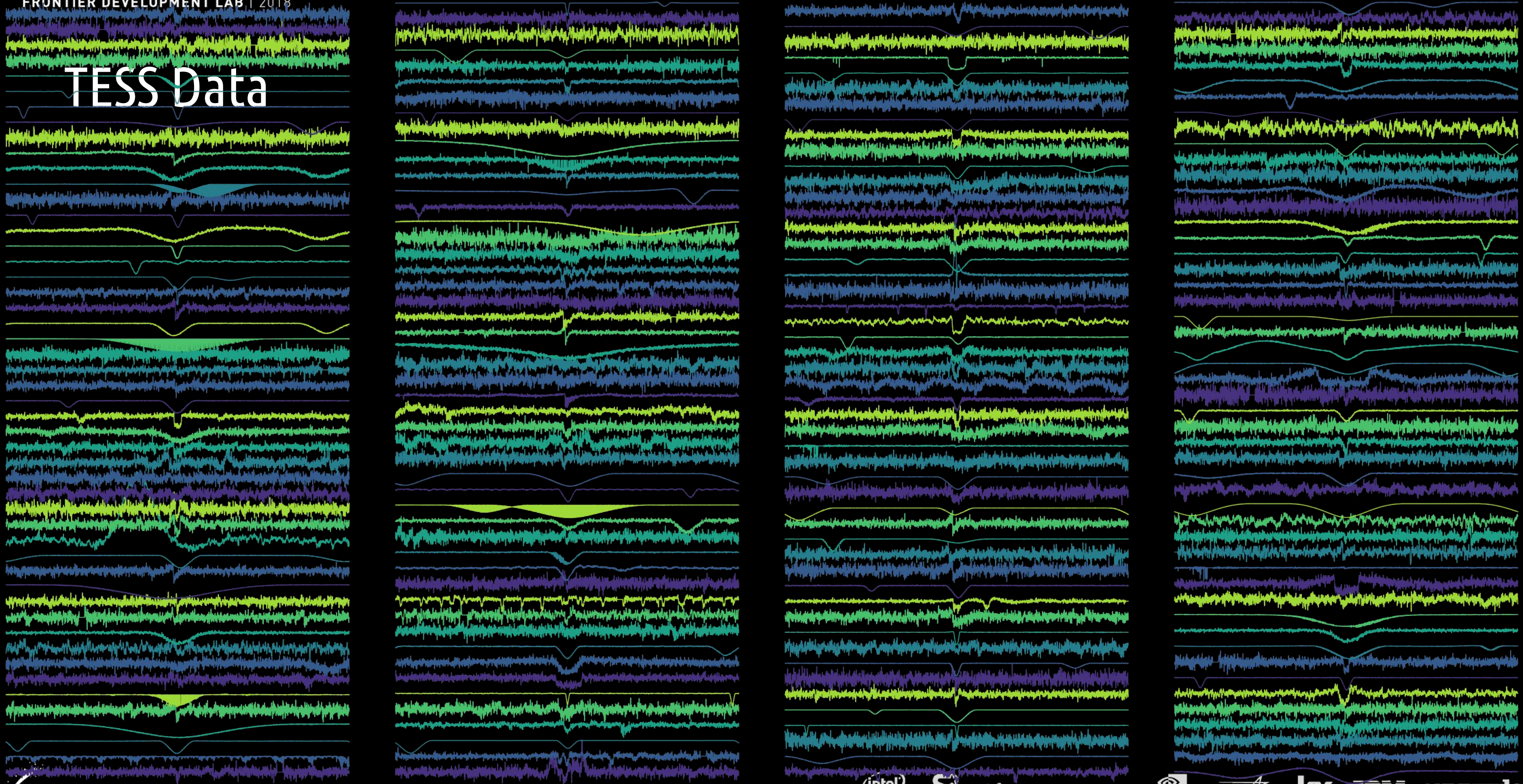


~16 000 lightcurves per sector

TESS Systematics



TESS Data

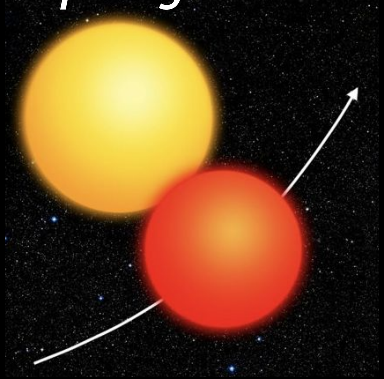


~5000 candidates per sector

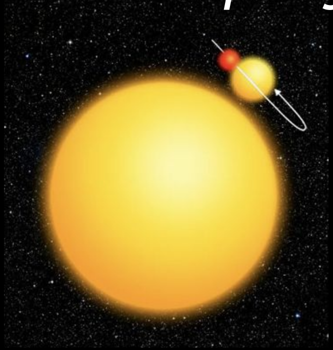
FDL

The problem: variety of false positives

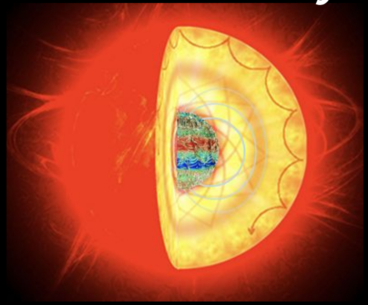
Eclipsing Binaries

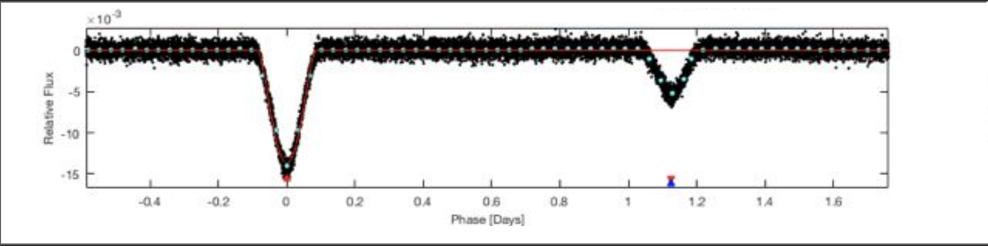


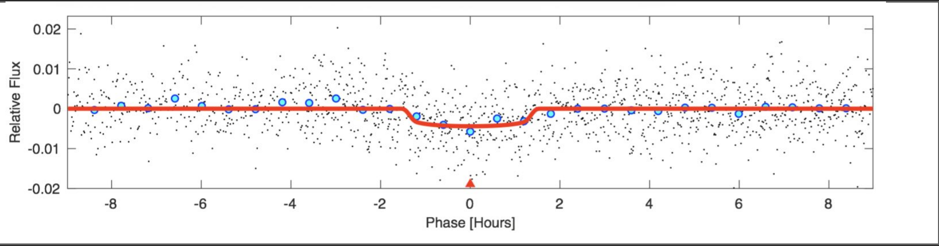
Background Eclipsing Binaries



Stellar activity







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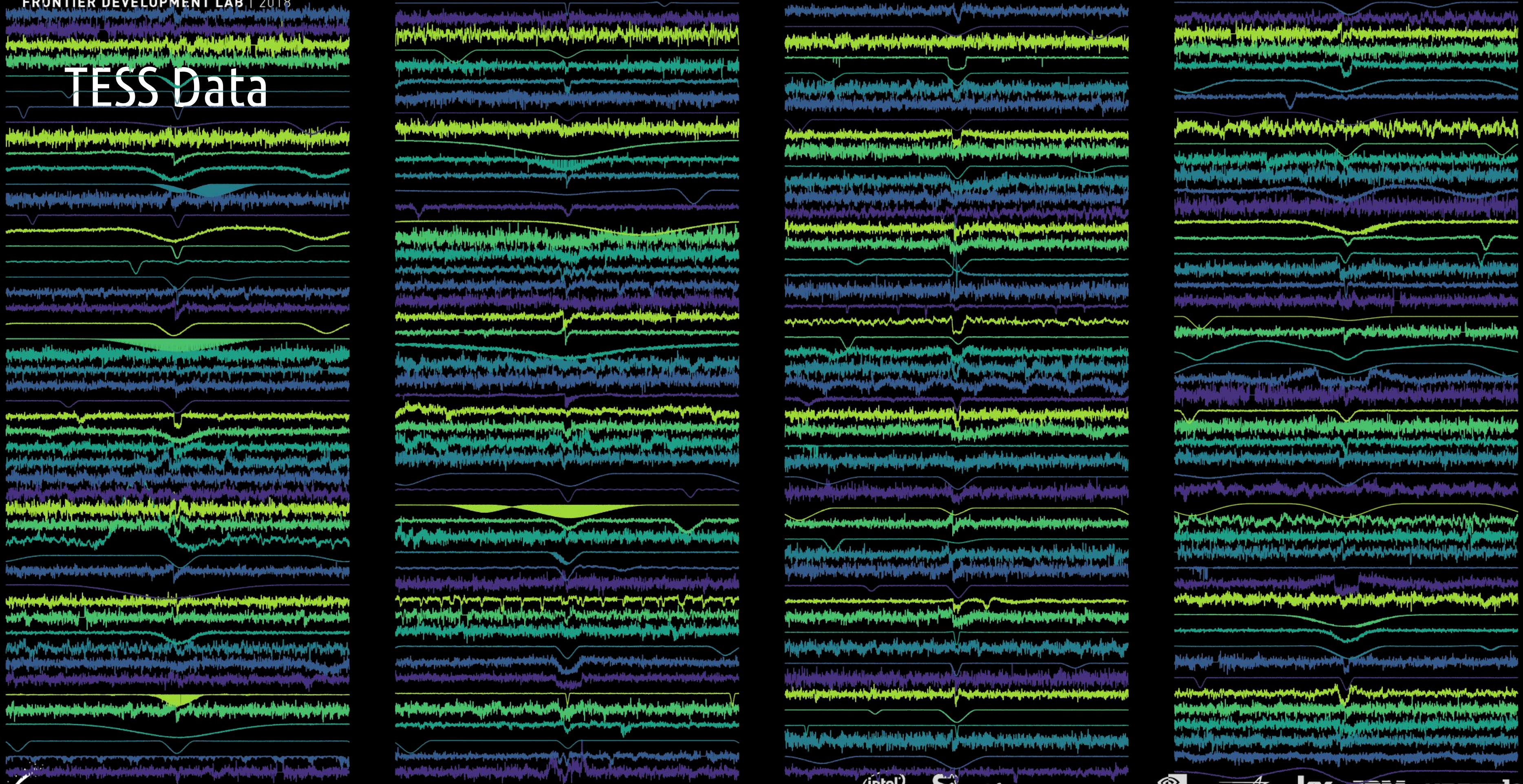

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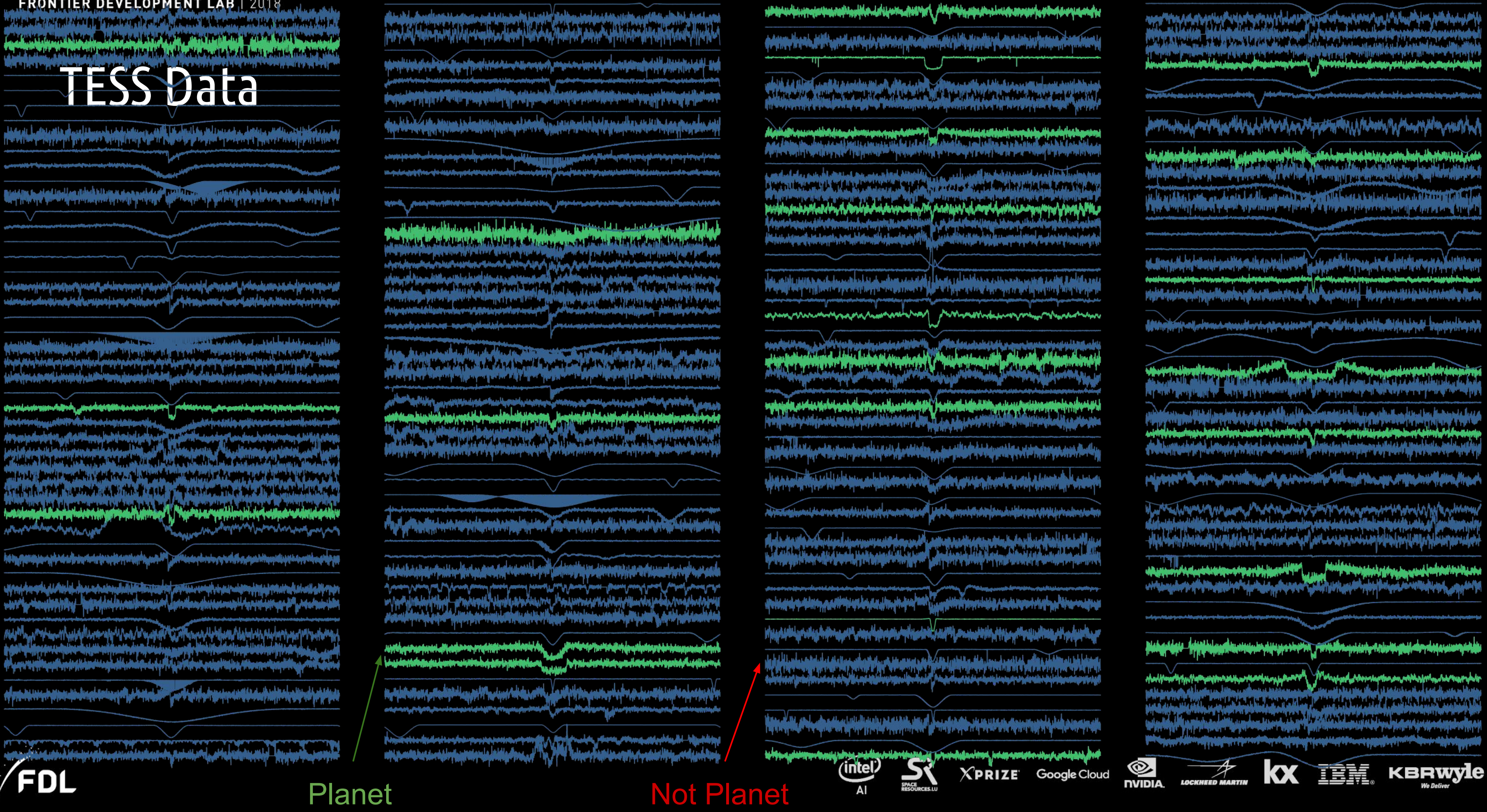

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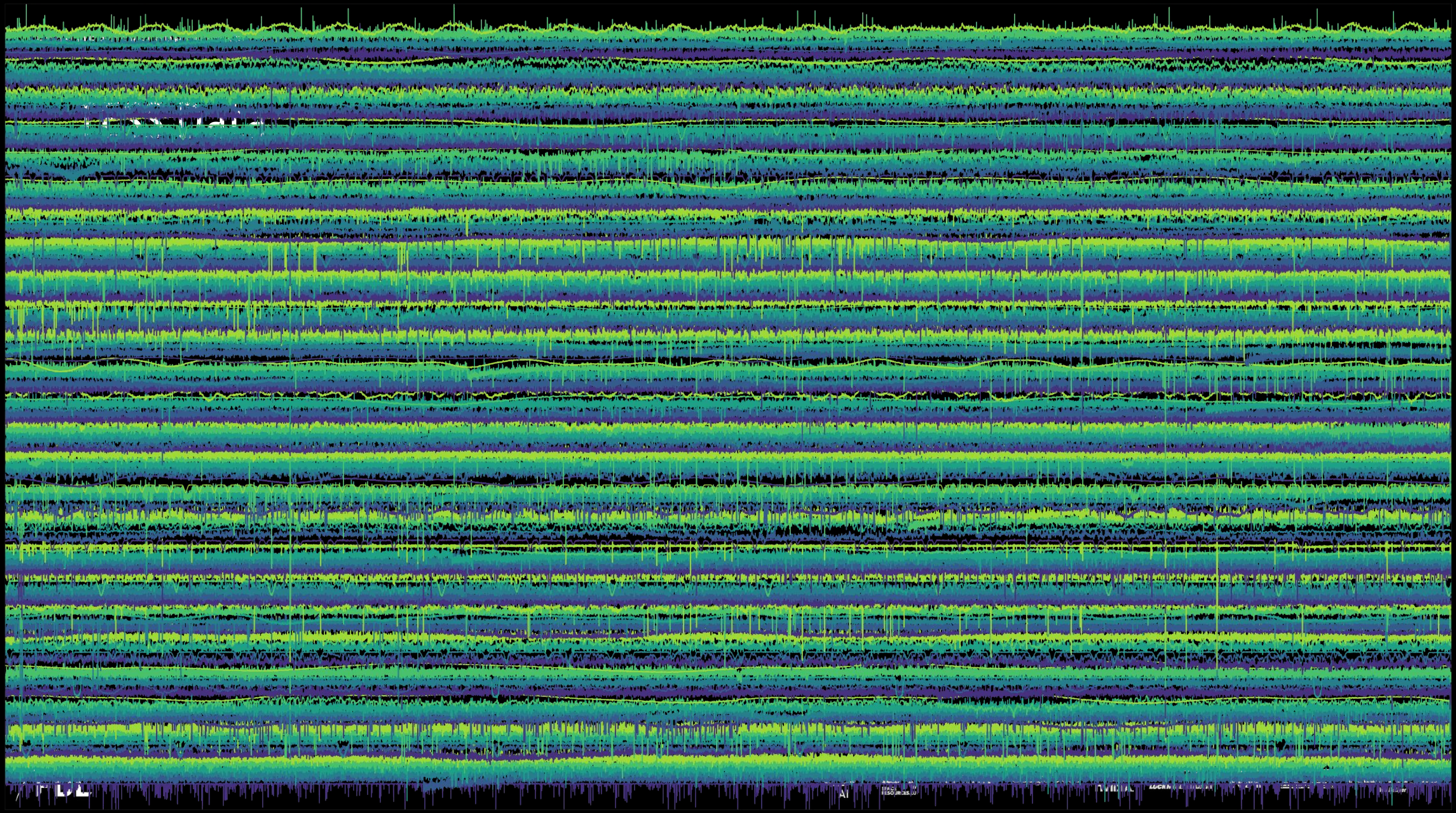

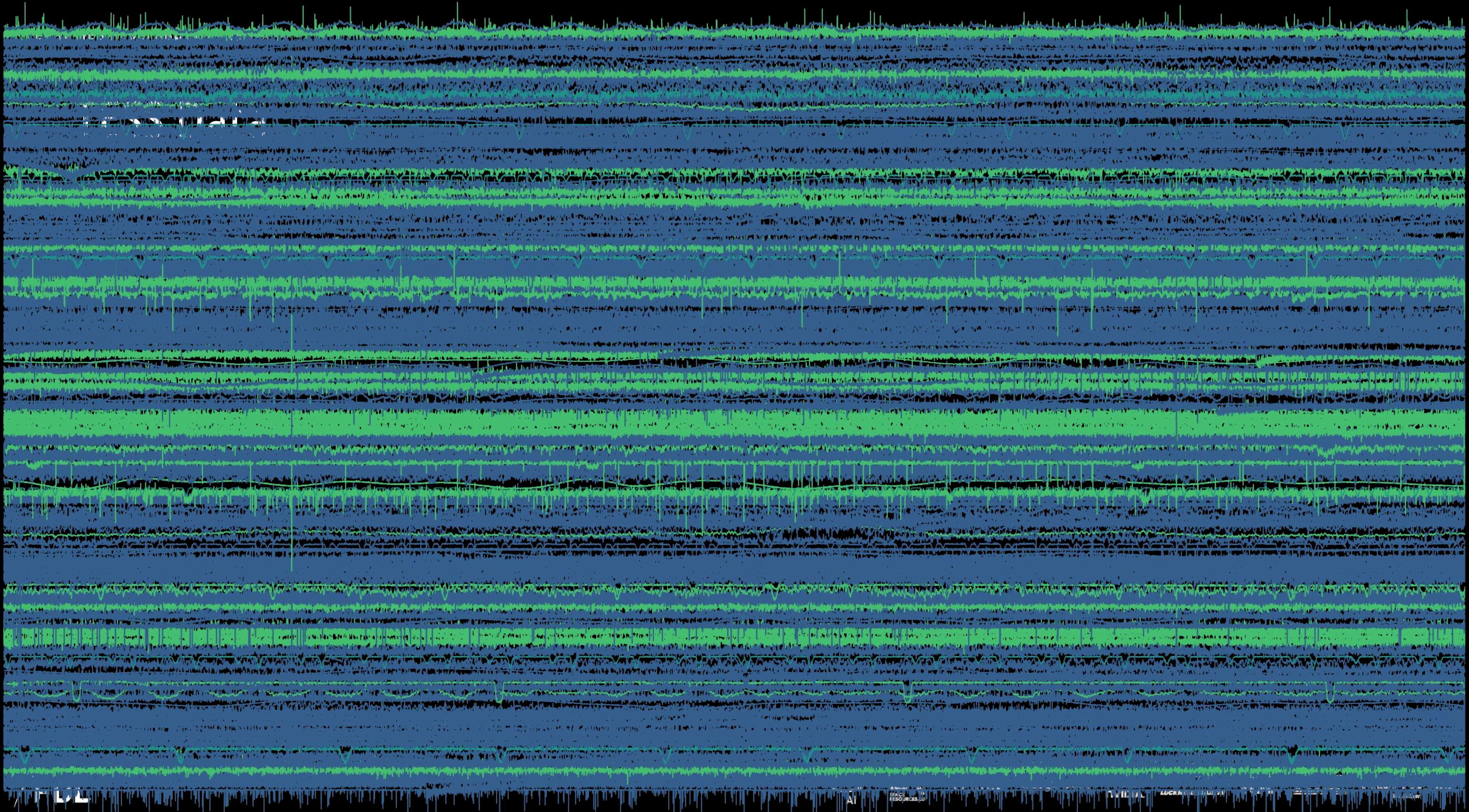

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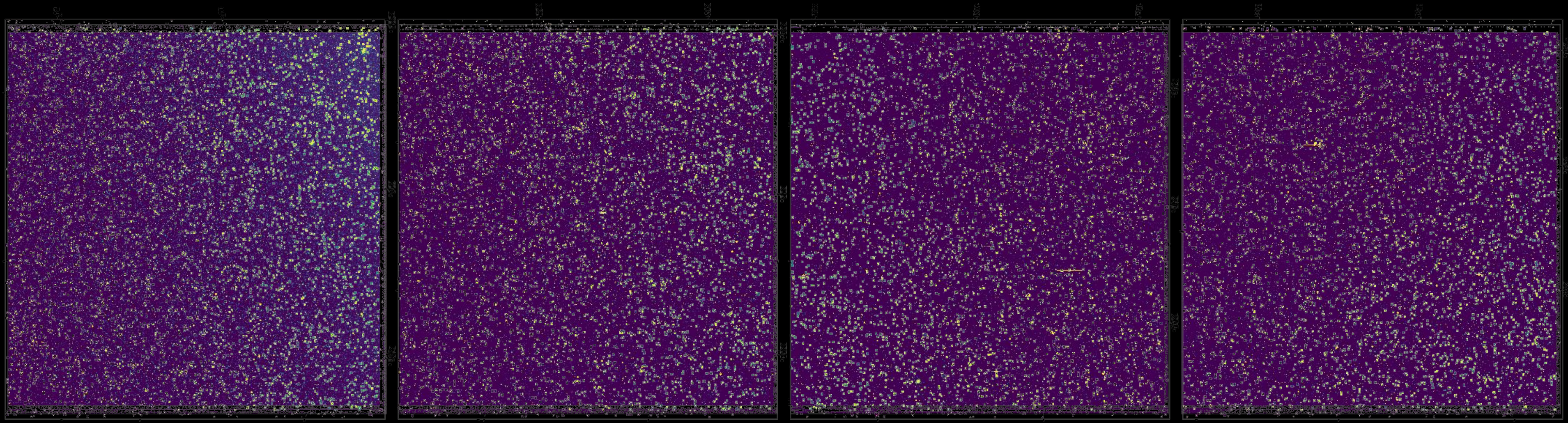

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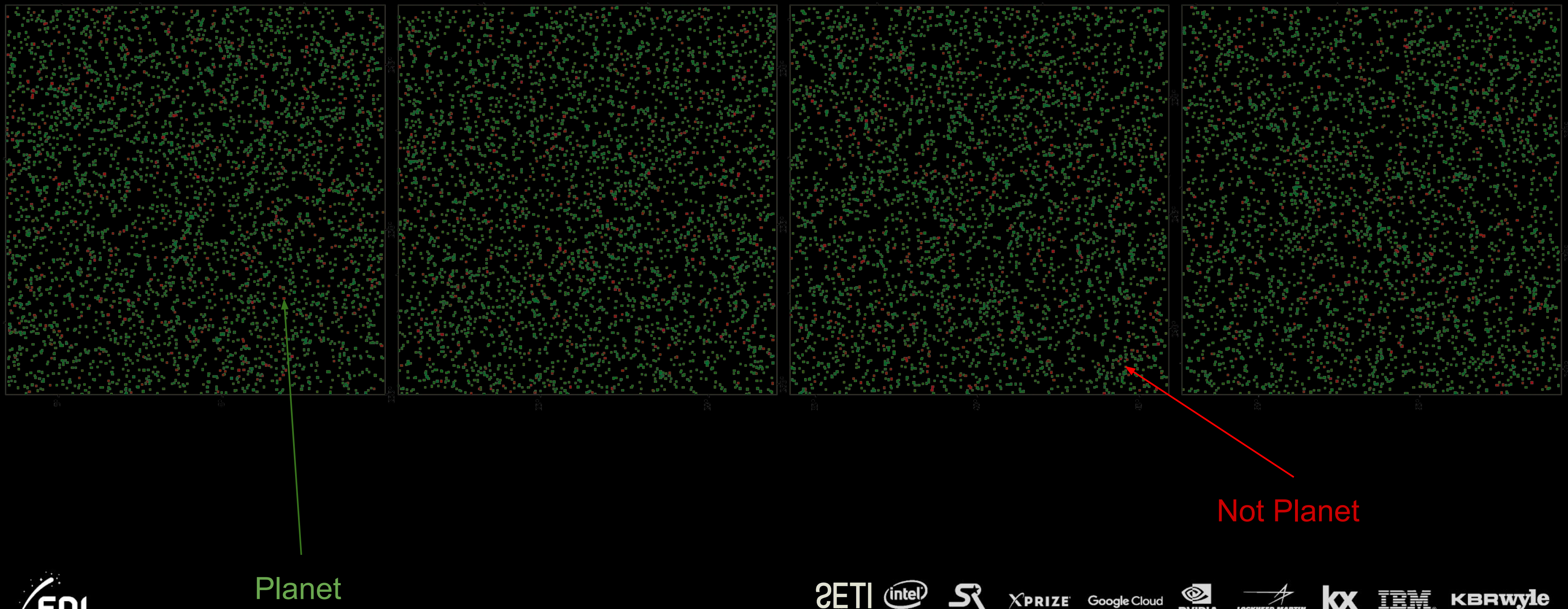


Current Classification Technique

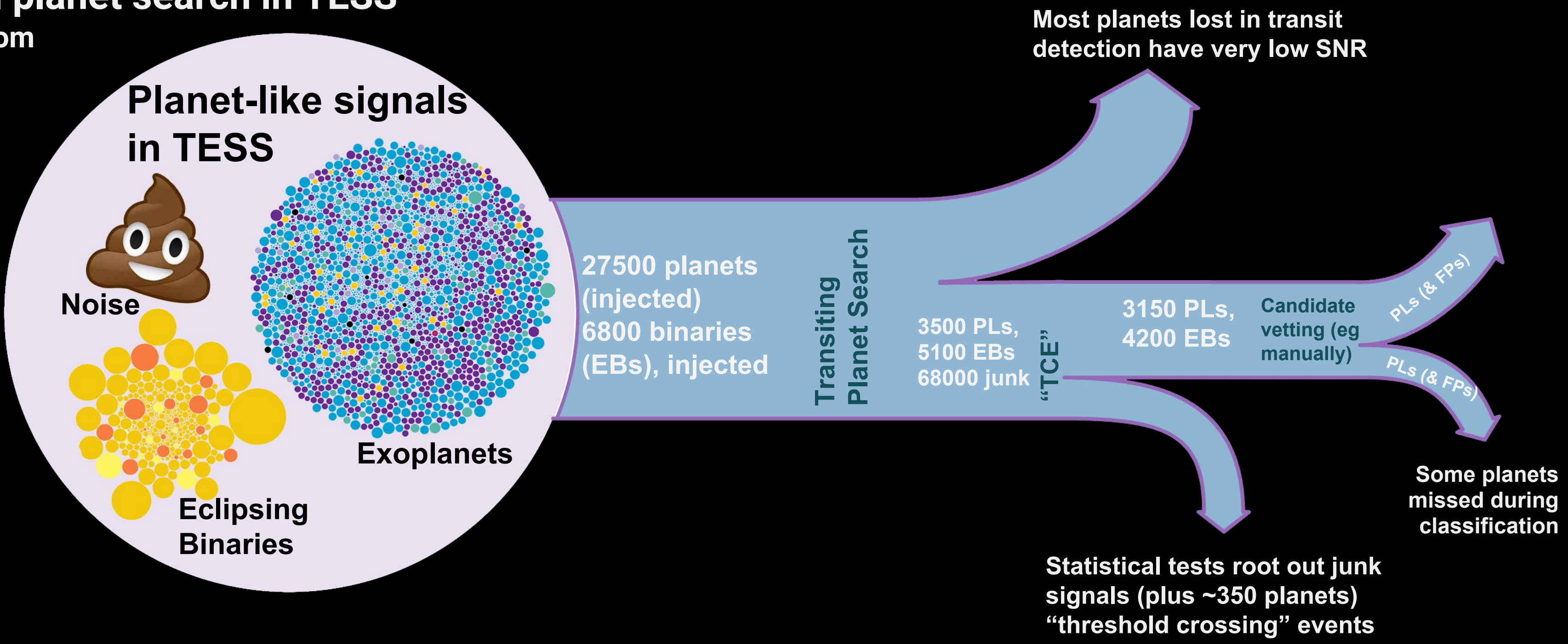
- Statistical/automated methods are used to whittle down candidates
- Manual vetting is still common
- Team of 18 humans: 94% accuracy
- ~300 human hours per sector


The telescopes are waiting...

From the detections...

Classical planet search in TESS

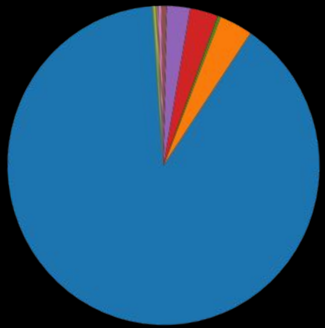
Numbers from TSOP-301 simulation



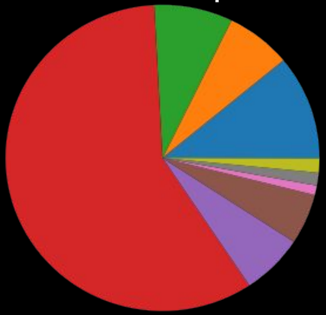
Classifying TESS Candidates

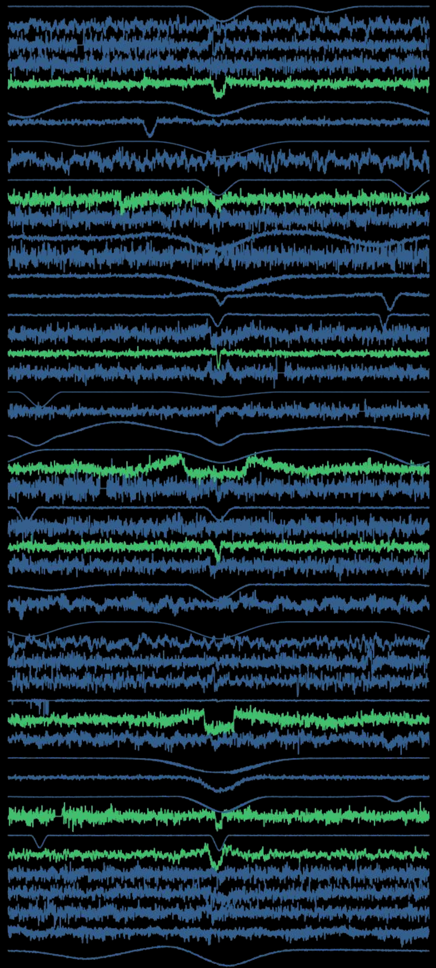
- TESS pipeline produces candidates in two tiers
- 70 000 initial detections from transiting planet search
- 30 000 pass statistical thresholds (TCEs)
- Only ~4000 planets (highly unbalanced)

TPS: ~3% planets



TCEs: ~14% planets

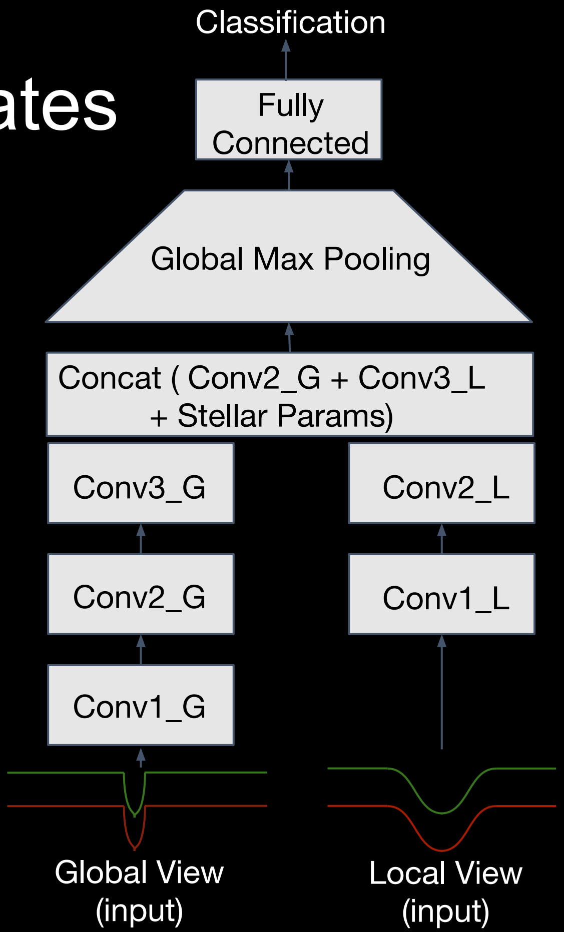


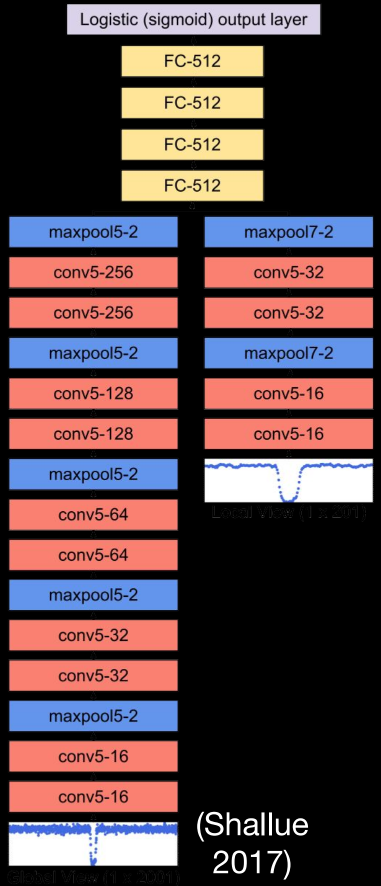


Classifying TESS Candidates

Adapted Shallue et al

- Made model smaller (0.06%)
- Added stellar parameters
- Added motion of star (centroid)
- Mini-batch balancing to account for label imbalance

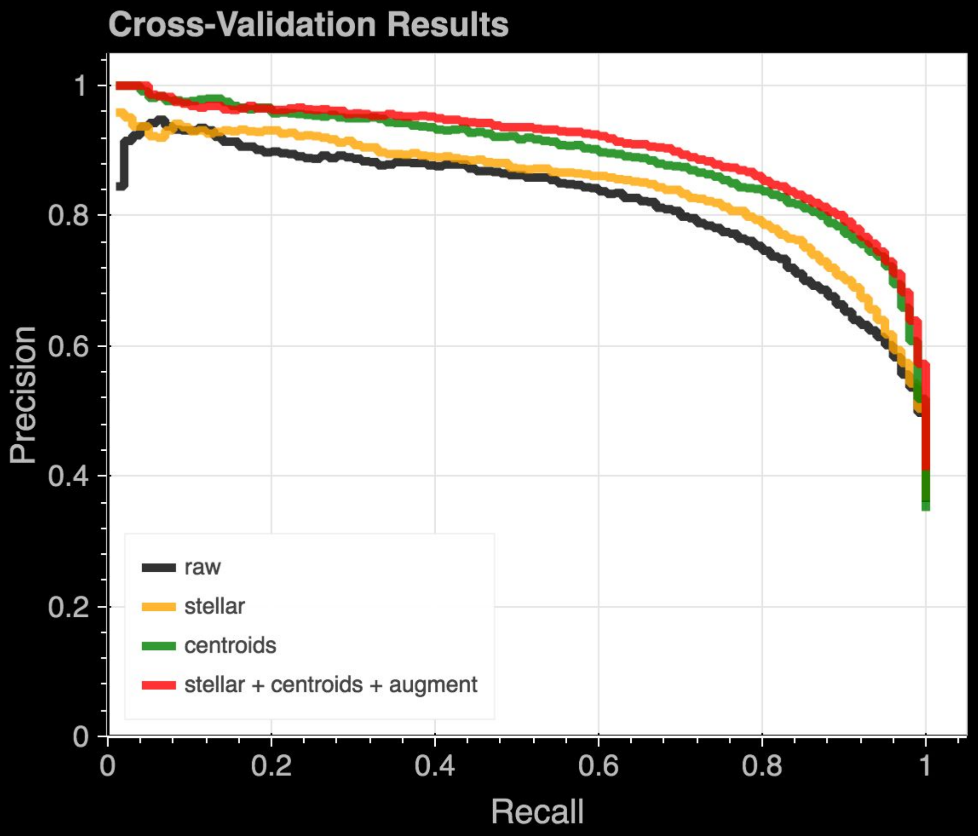




(Shallue 2017)

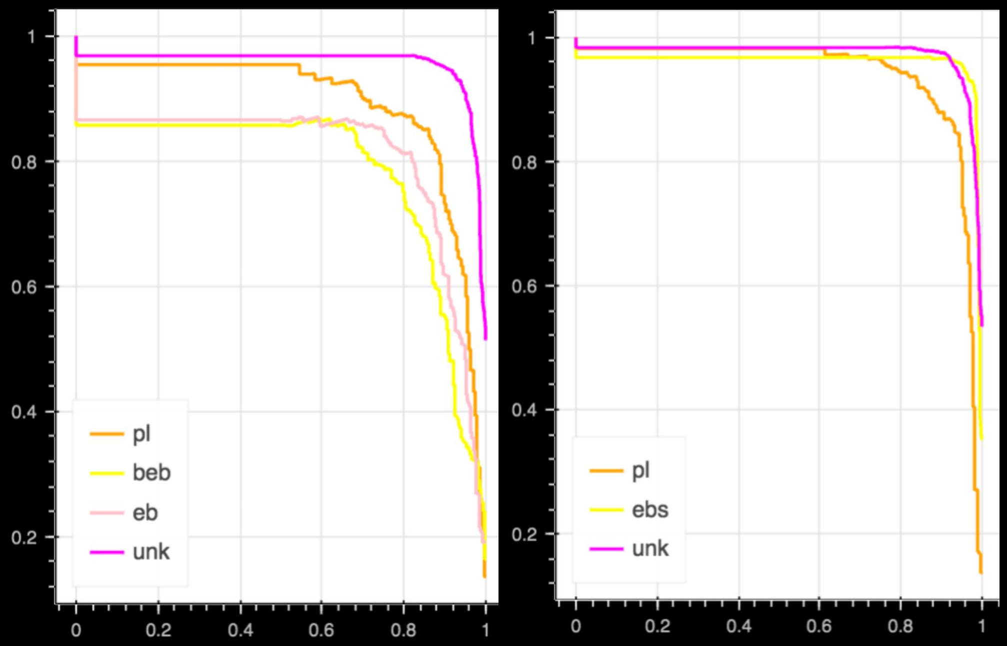
From the detections...

- Average precision on Kepler ~96%
- Recovers ~90 more planets than Shallue et al (on single model)
- Model is ~500 times smaller
- Similar precision on TESS data
- Can be run in minutes not hours!



From the detections...

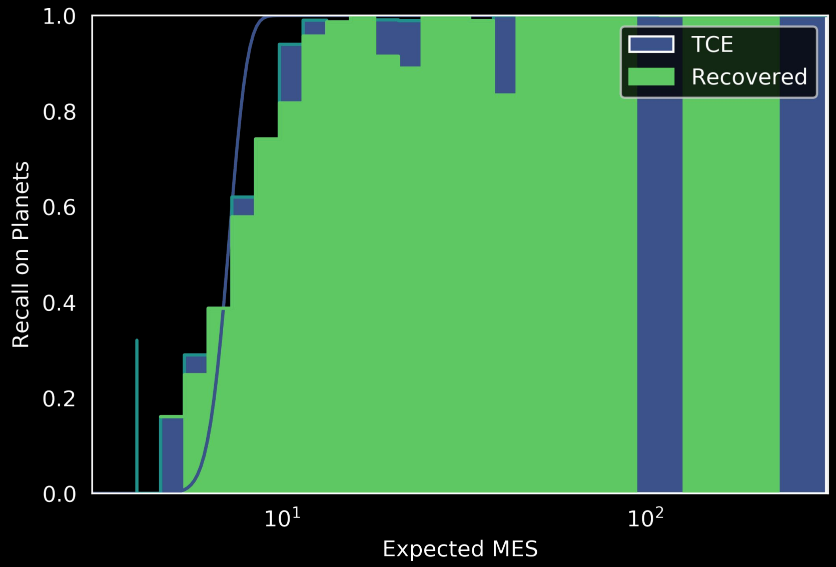
- Also developed multi-class models on TESS data.
- Useful for follow-up!
- 3-class > 4-class
- Slightly lower precision on planets.



From the detections...

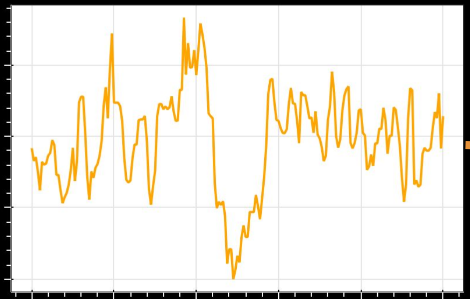
Kepler vs Shallue

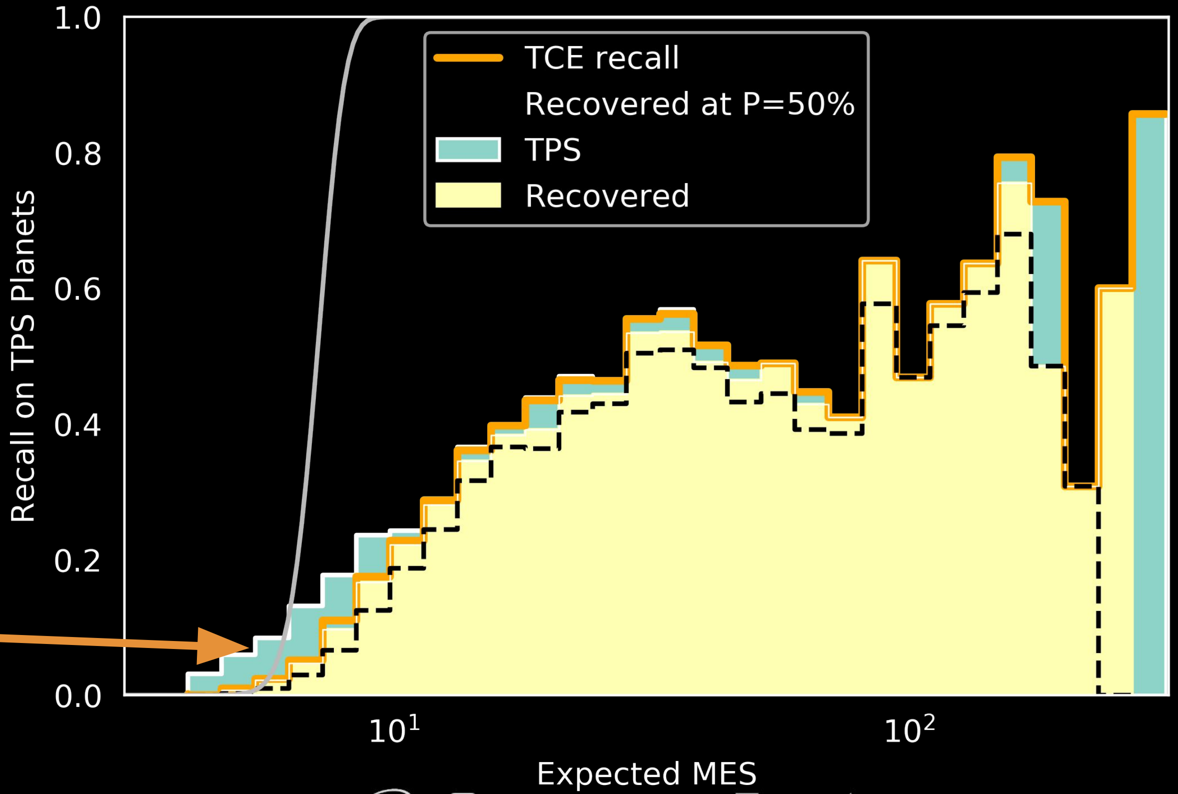
Up to 650 more planets recovered (at precision of 0.9 on single model)



From the detections...

- Can replicate the classical statistical threshold tests
- Recovered planetary signals missed by the classical tests





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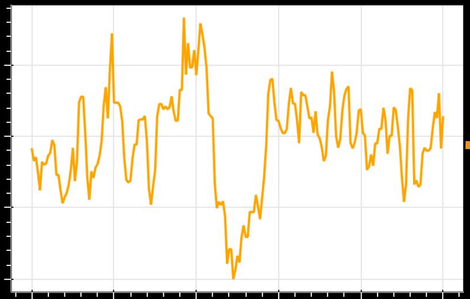
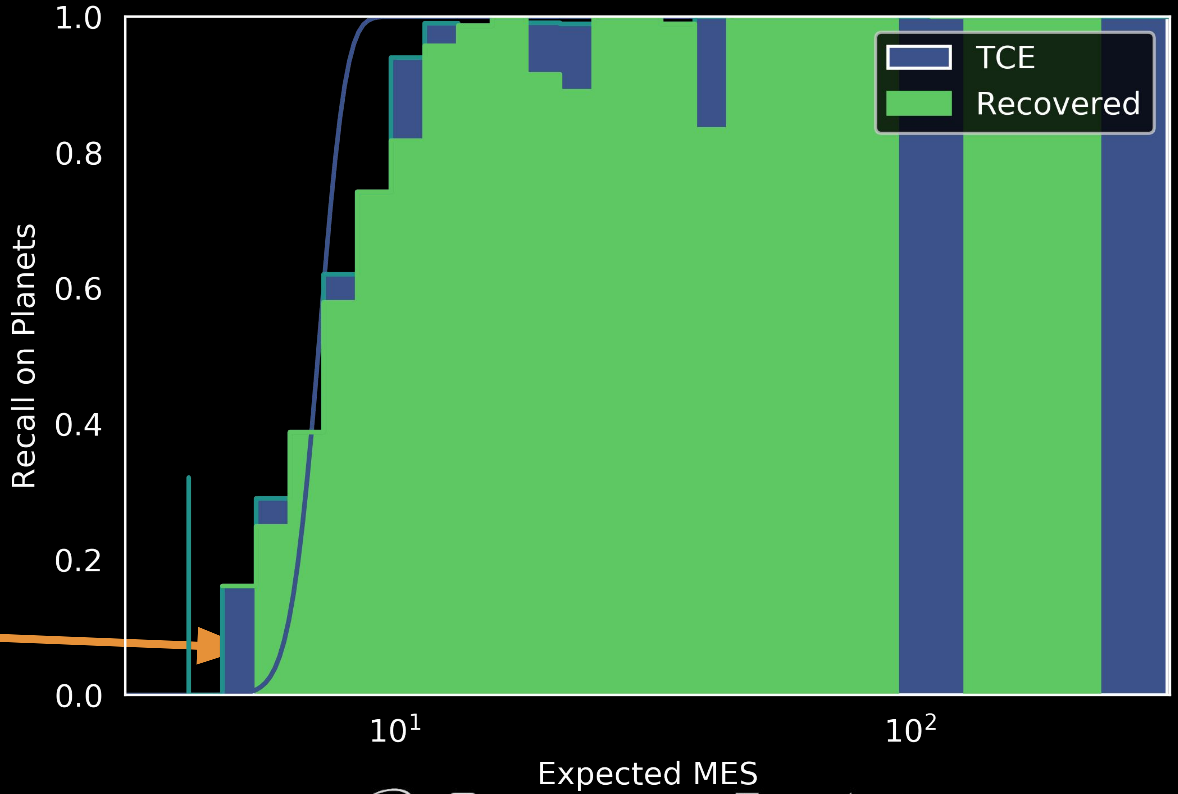
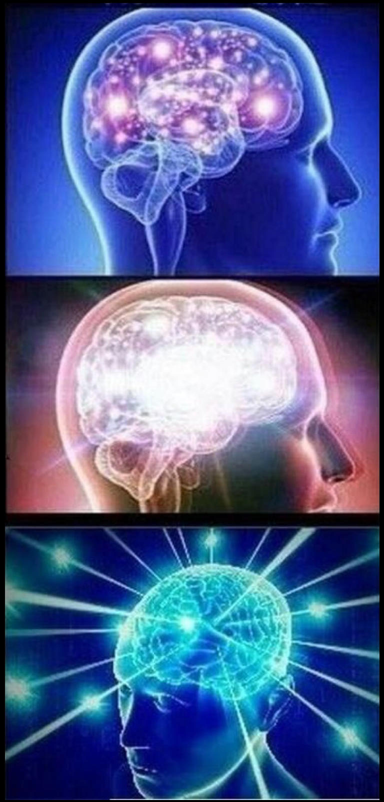


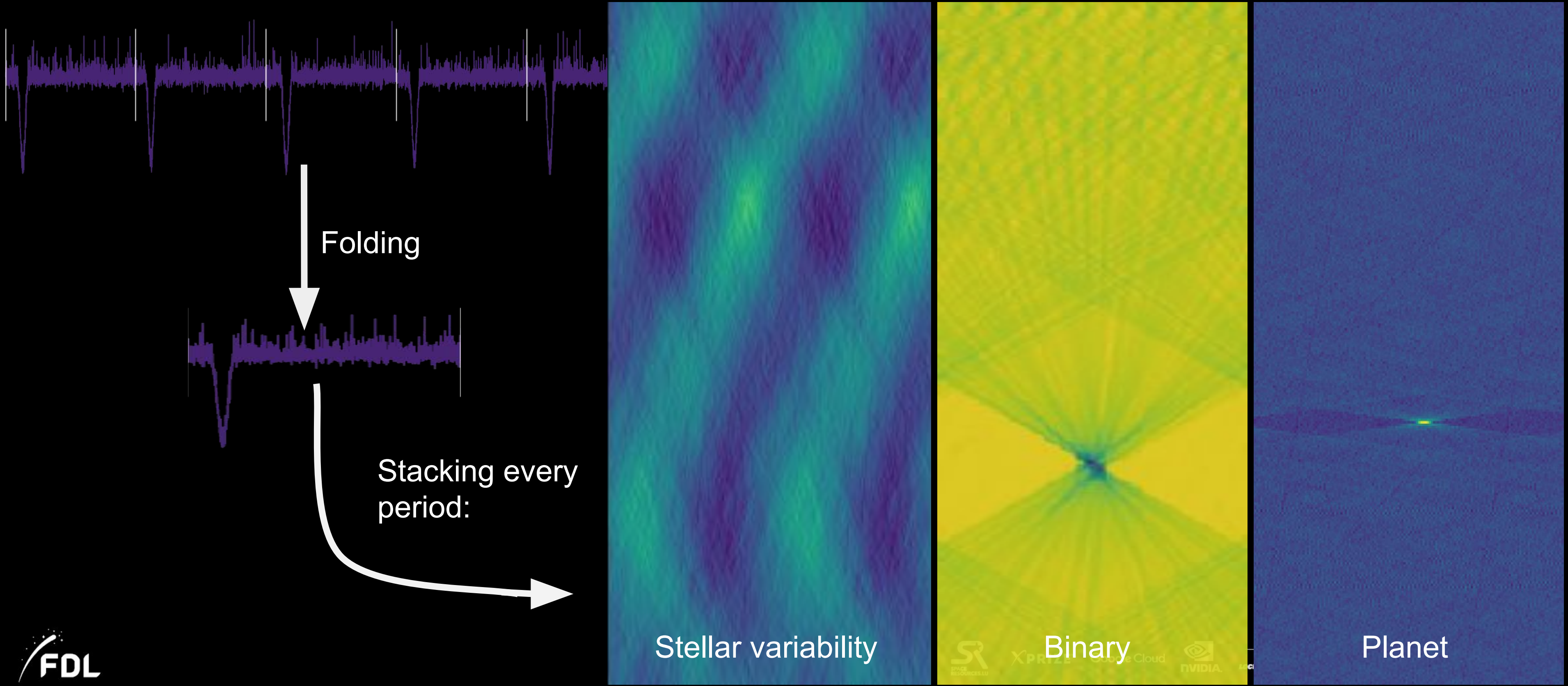


Future - applying to real TESS data

- Directly transfer network to real flight data…
  - Noisy data
  - Is the data (& systematics) the same as in training?
- Use human-vetted labels for TESS candidates…
  - Noisy labels
  - Slow
  - Exactly what we're trying to replace!
- Inject known signals into real flight data
  - Can train network rapidly with real data and noise.
  - Simulations and network re-training can be part of pipeline.

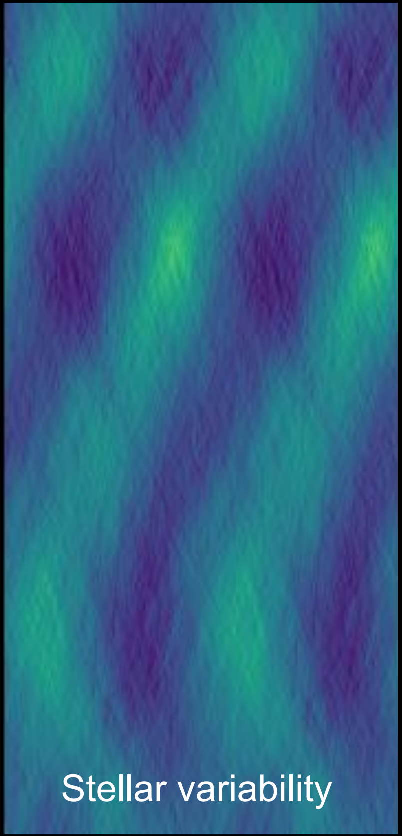


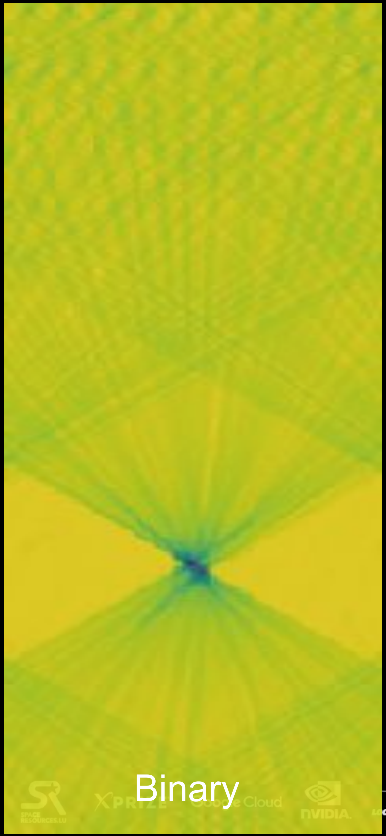
From the lightcurve...

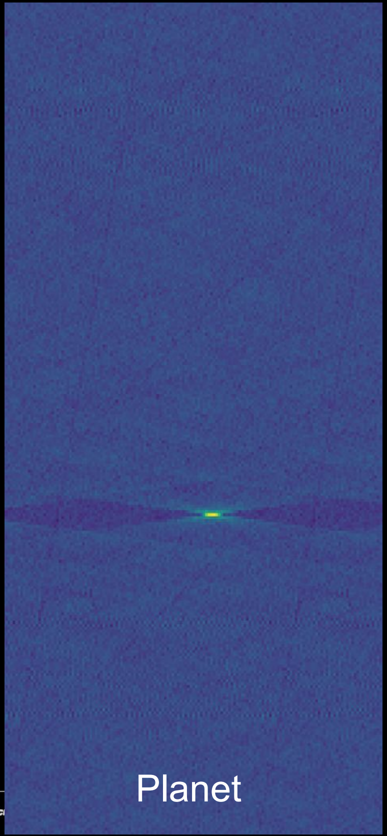


From the lightcurve...

- Applies ResNet50
- 91% accuracy on Kepler candidates
- Promising but need more time.







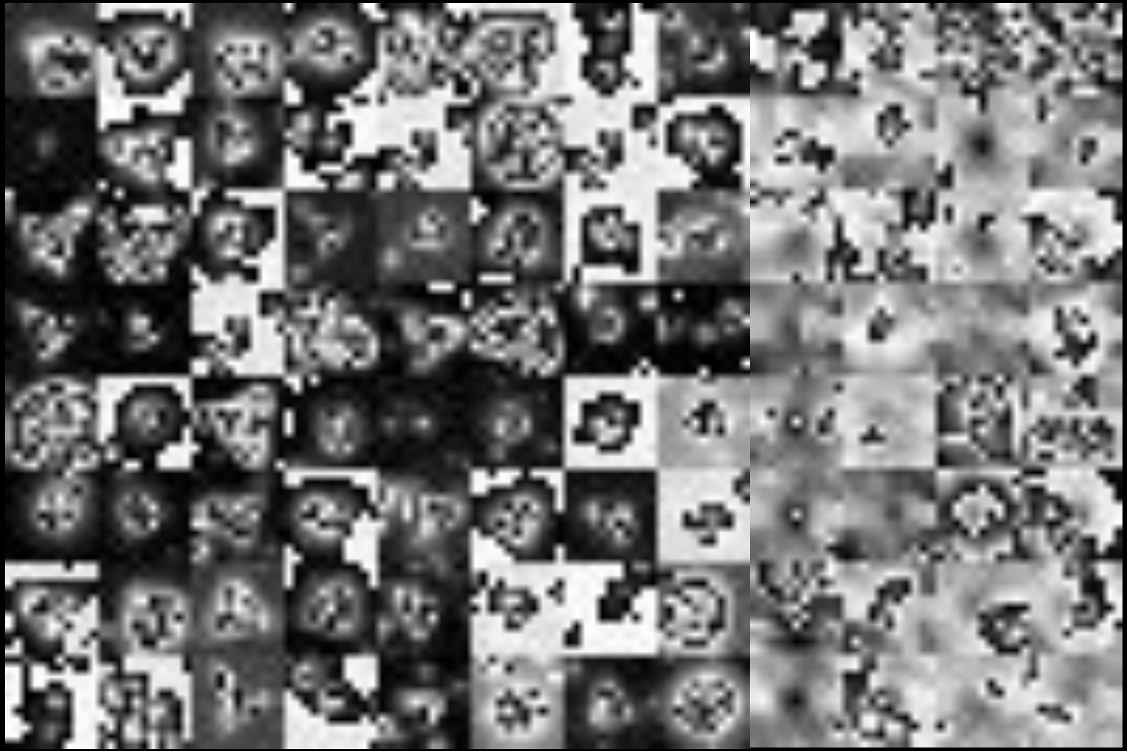
From pixels...

64 000 month-long videos

Lots of noise!

Promising approach which could by-pass TESS pipeline…

But needs more work.



Summary

- Classify TESS planets **faster** & **more precisely** than previous approaches.
- Innovative new avenues for planet hunting direct **from light curves & pixels**

Megan Ansdell, Yani Ioannou, **Hugh Osborn**, Michele Sasdelli
+ Jeff Smith, Jon Jenkins, Doug Caldwell

Thanks

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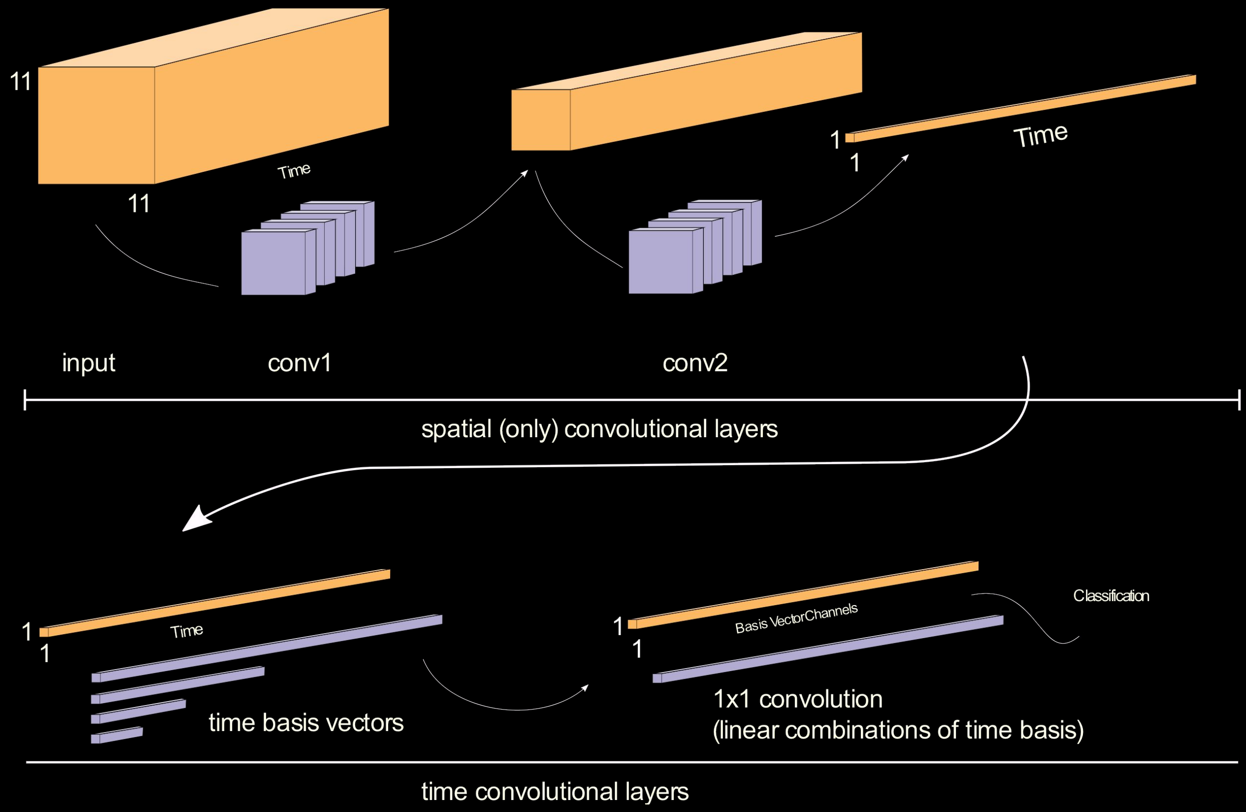
From pixels...

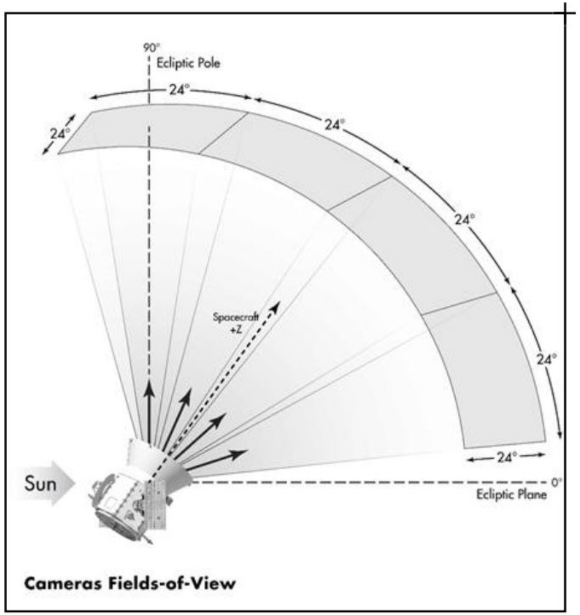
64 000 videos of stars

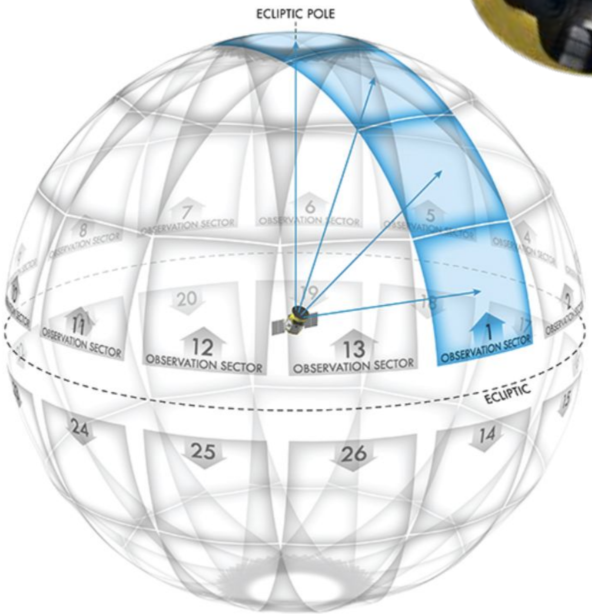
Promising approach which could by-pass TESS pipeline…

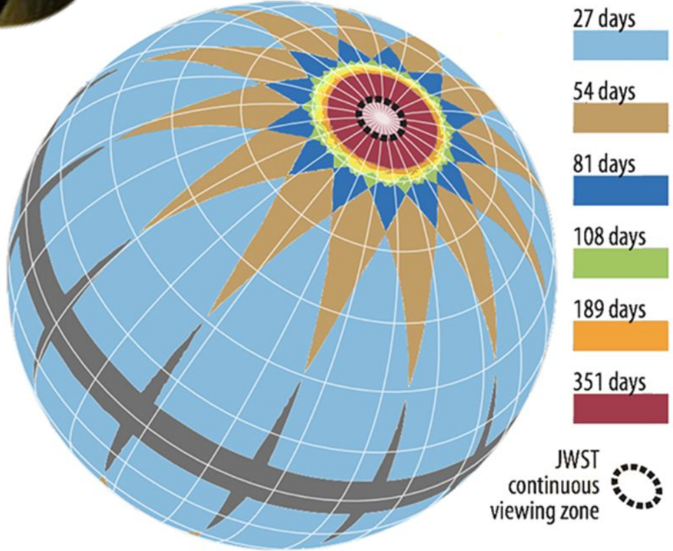
But needs more work



The data: TESS mission

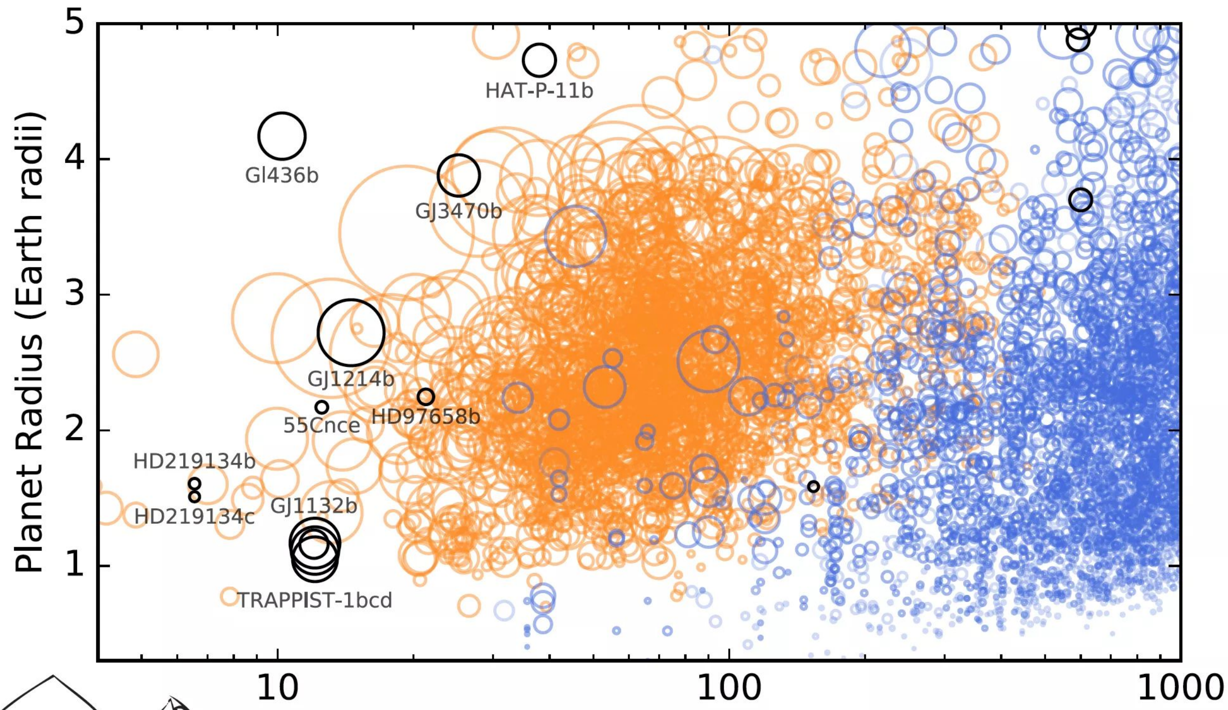


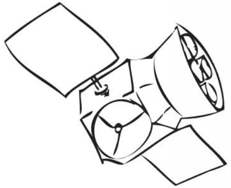


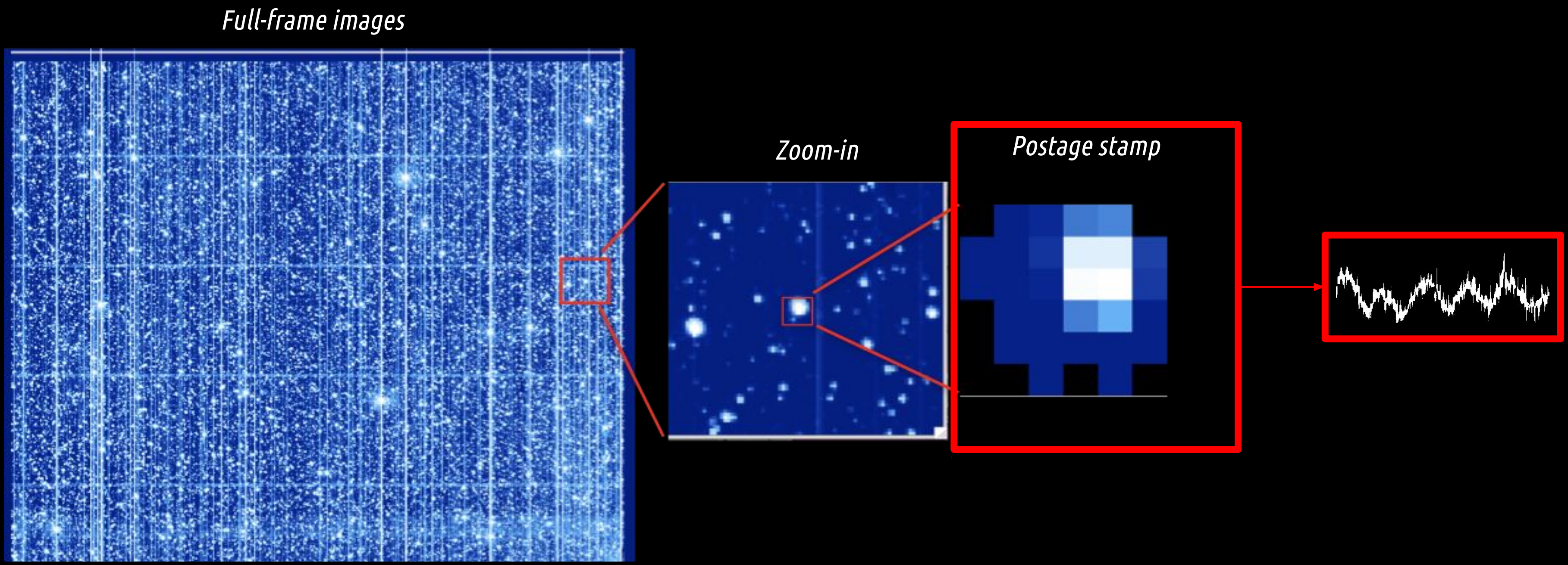


TESS

Exoplanets around nearby stars






Full-frame images
Zoom-in
Postage stamp

Incremental: Classify planet candidates detected by the pipeline

- Train a Neural Network on candidate planets (TCEs) detected by the pipeline Transiting Planet Search

- Use heavily pre-processed domain data generated by the pipeline.

In Shallue et al 2017:

Full lightcurve

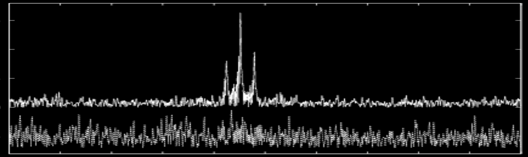
Zoomed-in lightcurve

New Input Datasets:

Centroids (x & y)

Stellar Properties

Data augmentation



Incremental: Classify planet candidates detected by the pipeline

Improvements on Shallue, 2017:

- More input datasets
- Multiple false-positive classes
- Use data balancing
- Augment light curves to increase training examples.
- Lighter NN
-

In Shallue et al 2017:

Full lightcurve

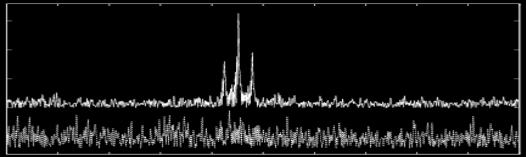
Zoomed-in lightcurve

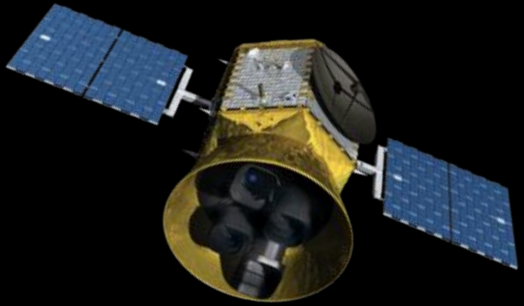
New Input Datasets:

Centroids (x & y)

Stellar Properties

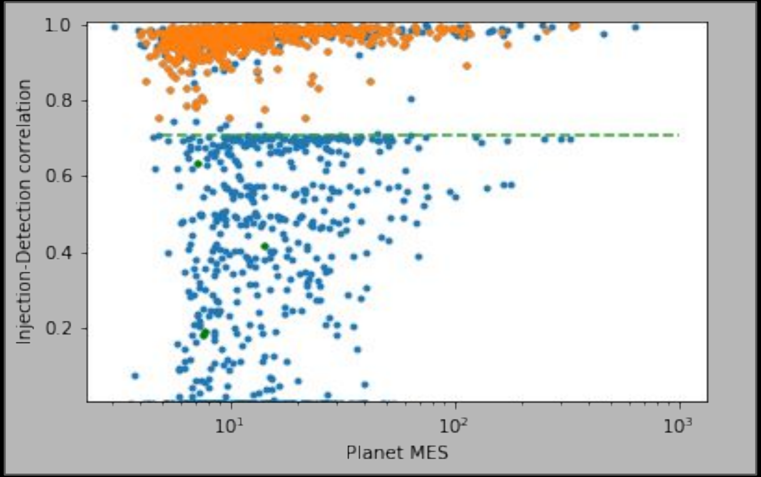
Frequency-space data

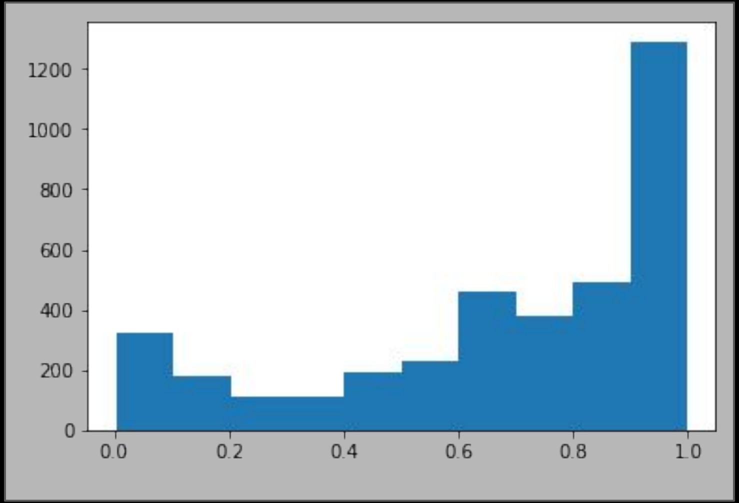


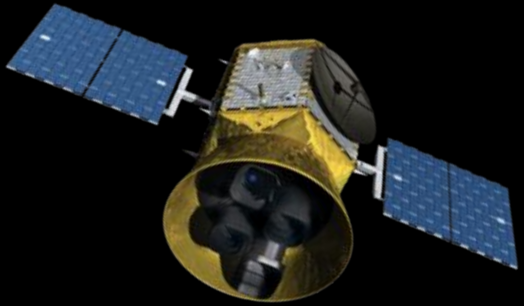


Ongoing work:

- Labels not necessarily intuitive.
- Modified “correlation” metric between injections and detections to include period multiples.
- Still issues with high-SNR planets not being detected







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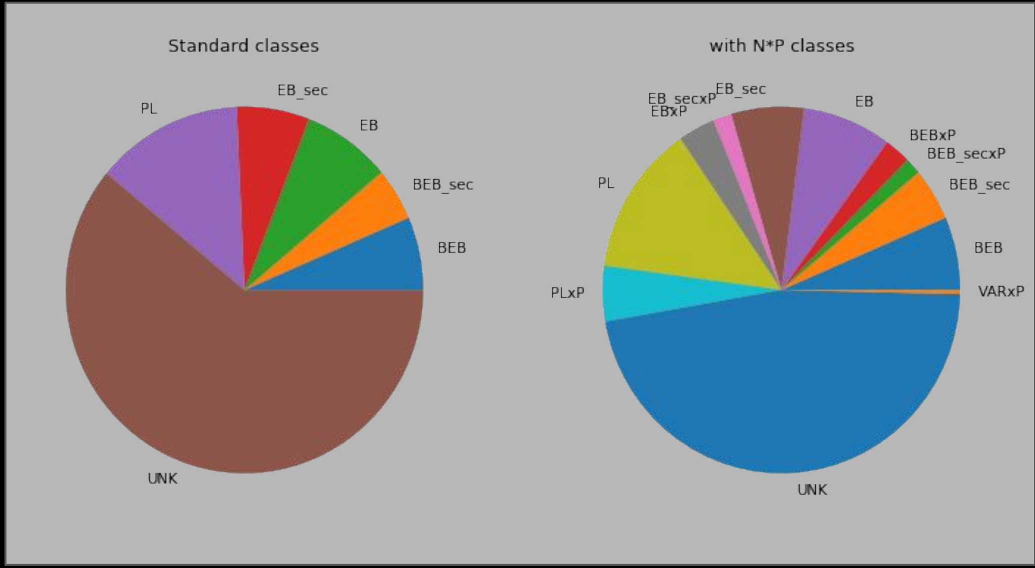
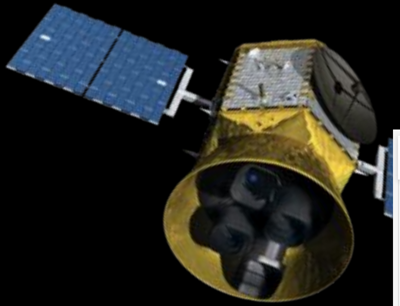
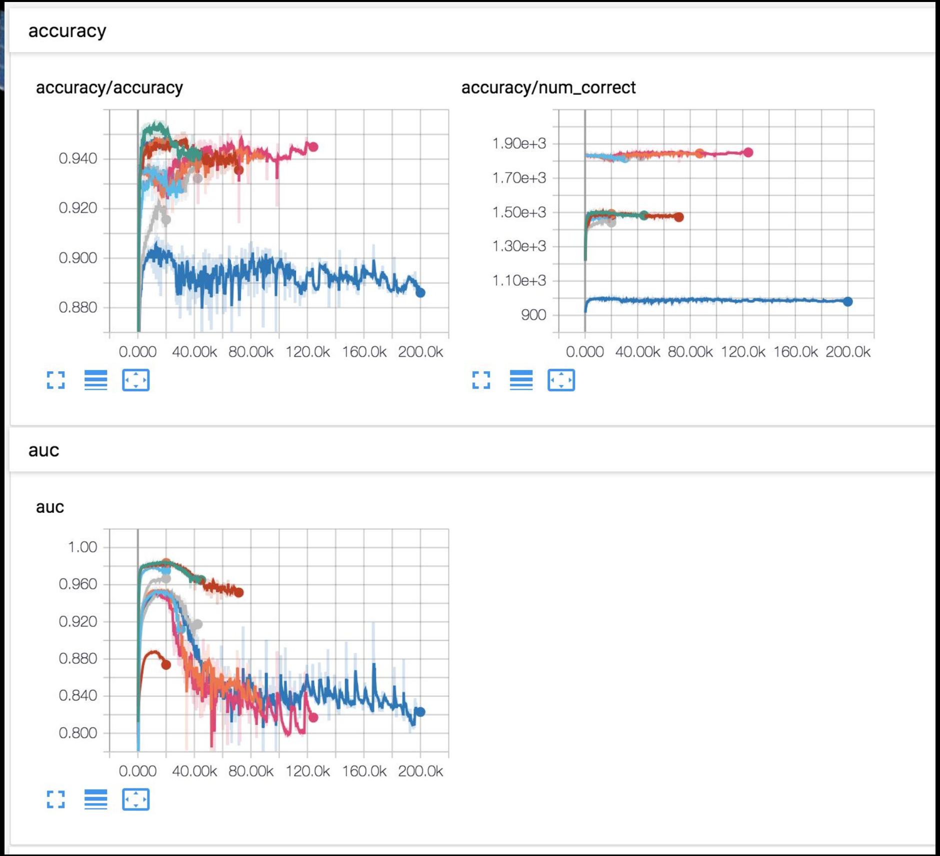
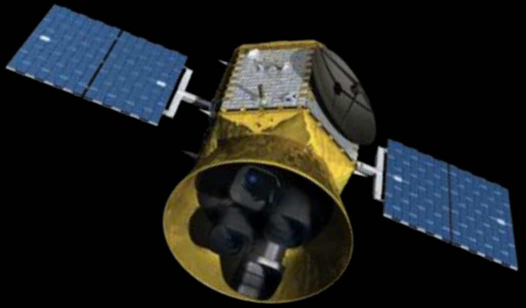




Ongoing work:

- Converted Shallue code from Kepler to TESS
- Improvement with centroids
- Also improved with modified smoothing (spline) techniques.
- Models being trained
- Stellar parameters and frequency space data to be tested and added





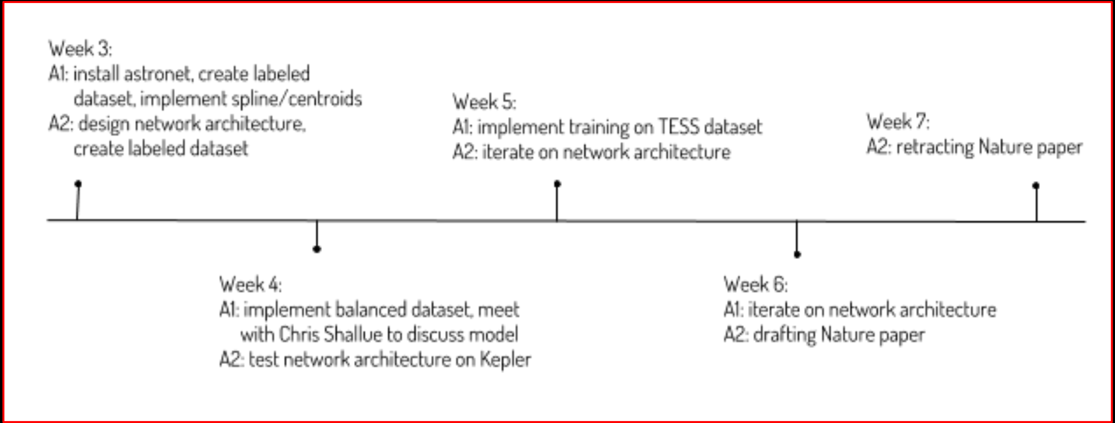
Next steps...

Week 4:

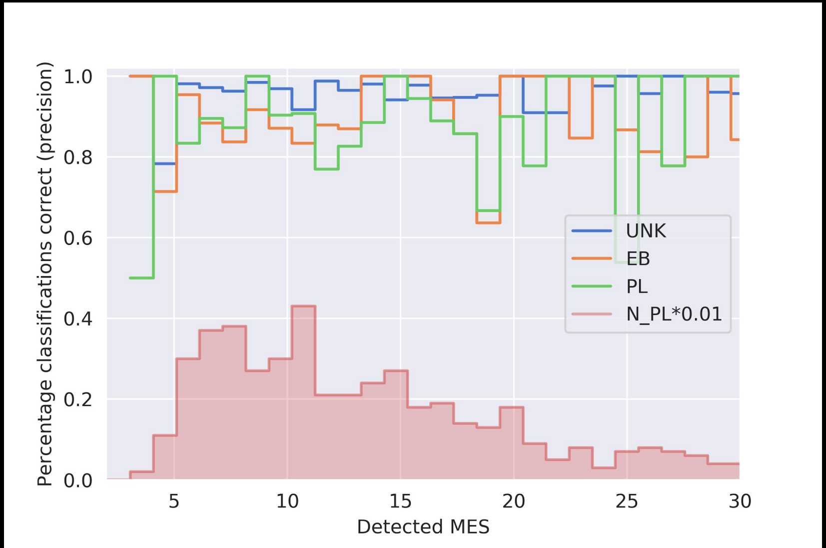
- *Avenue 1*: Implement balanced labels
- *Avenue 2*: Test design architecture with Kepler

Week 5:

- *Avenue 1*: Implement training based on TESS data
- *Avenue 2*: Iterate on model/architecture



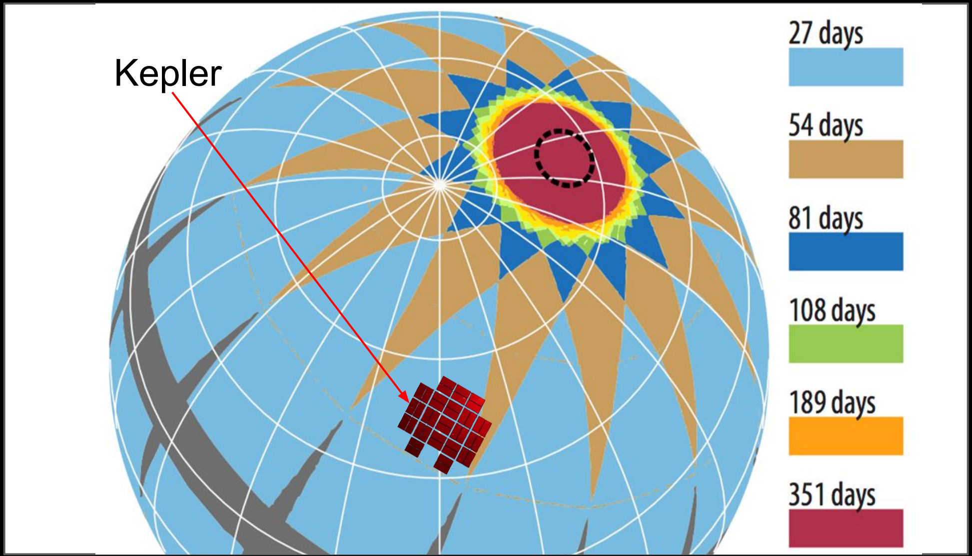
Results on TESS

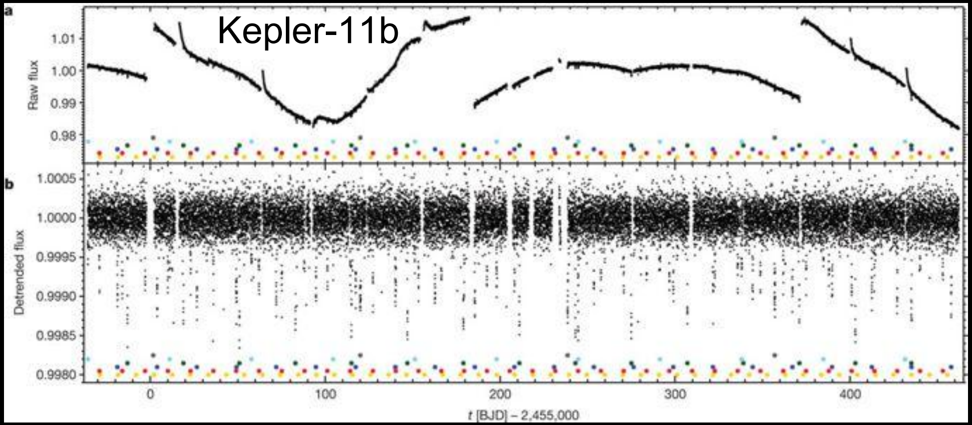


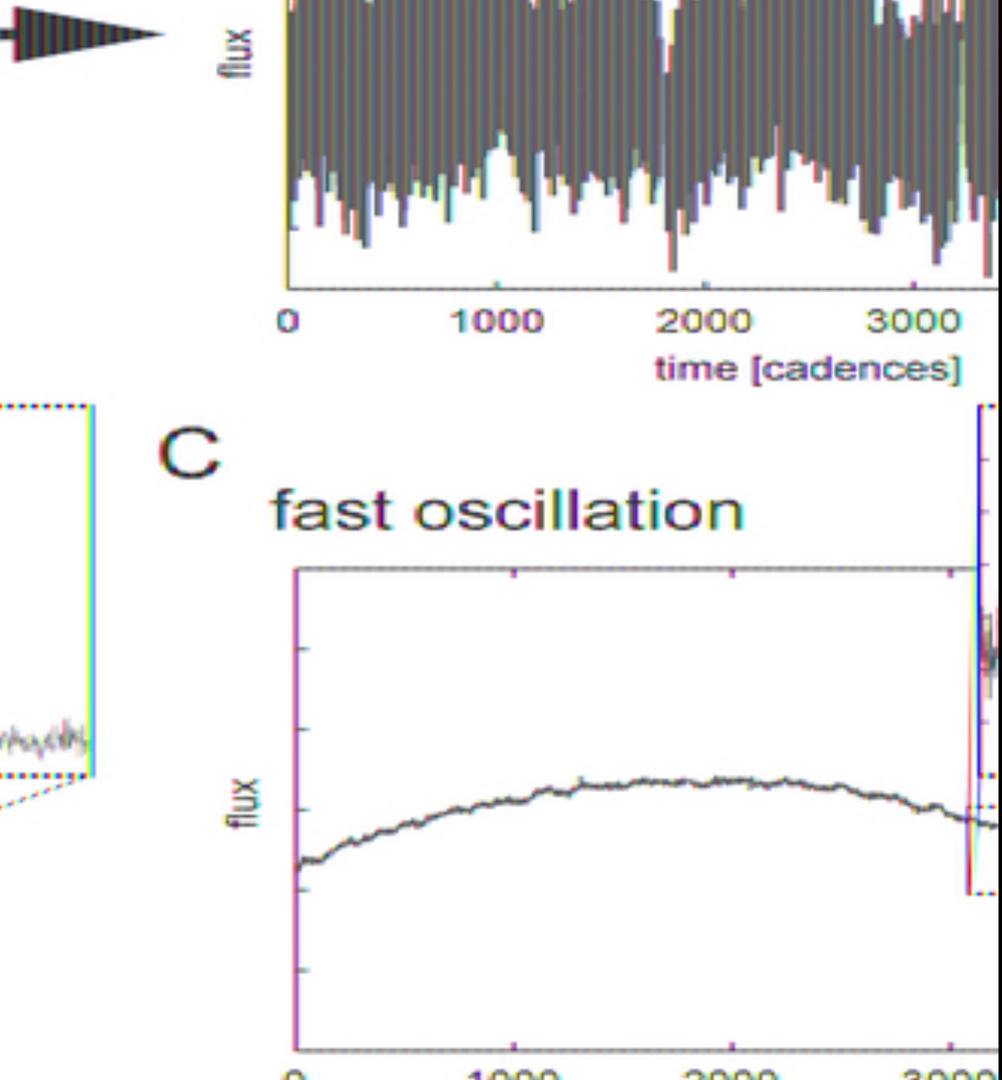
Kepler Data

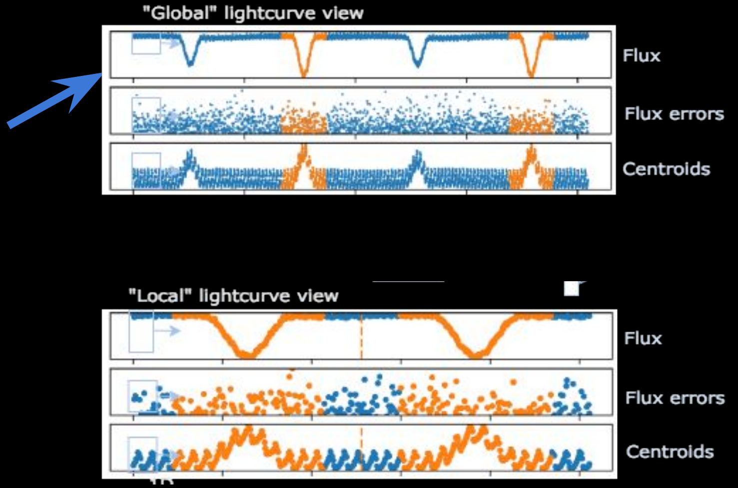
Real data but noisy labels

- 150 000 lightcurves
- Lightcurves 4 years in duration
- ~4 000 planets (candidates & confirmed)
- Can augment data to TESS-like 27-day campaigns (up to 7.8 million ‘targets’)

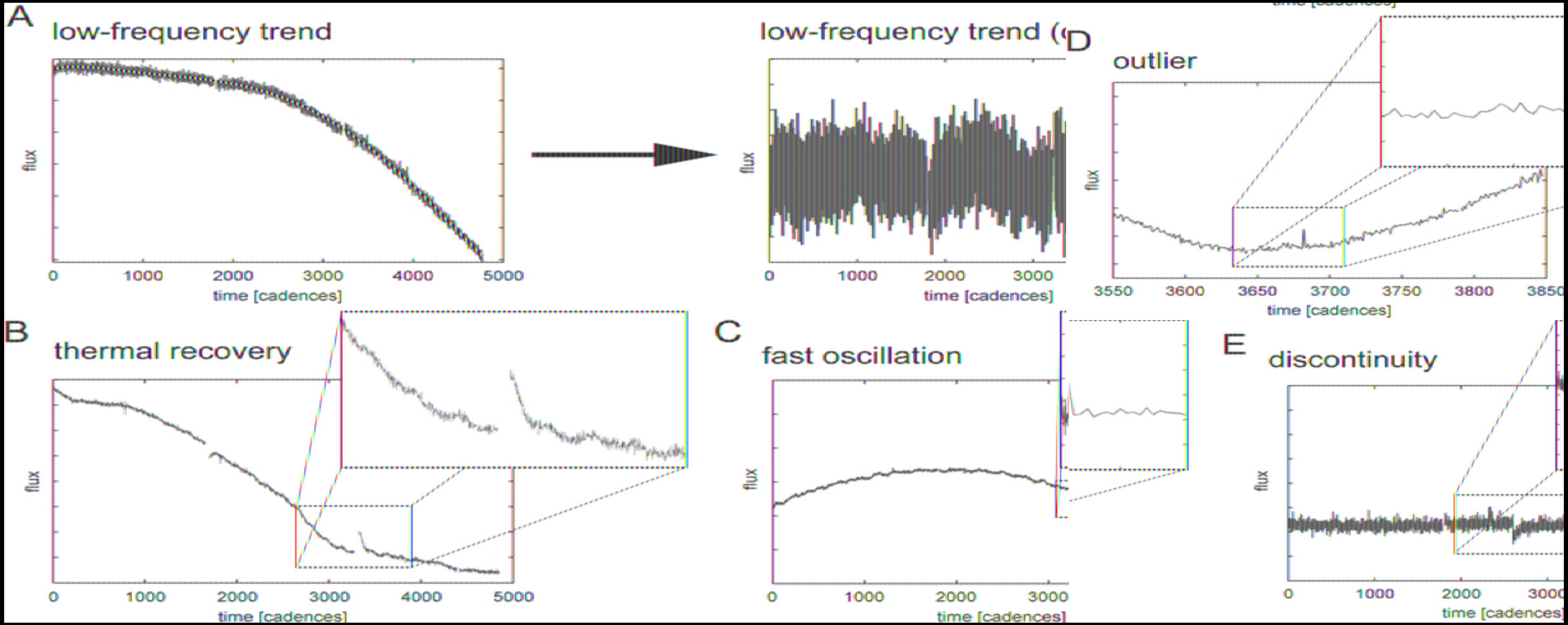




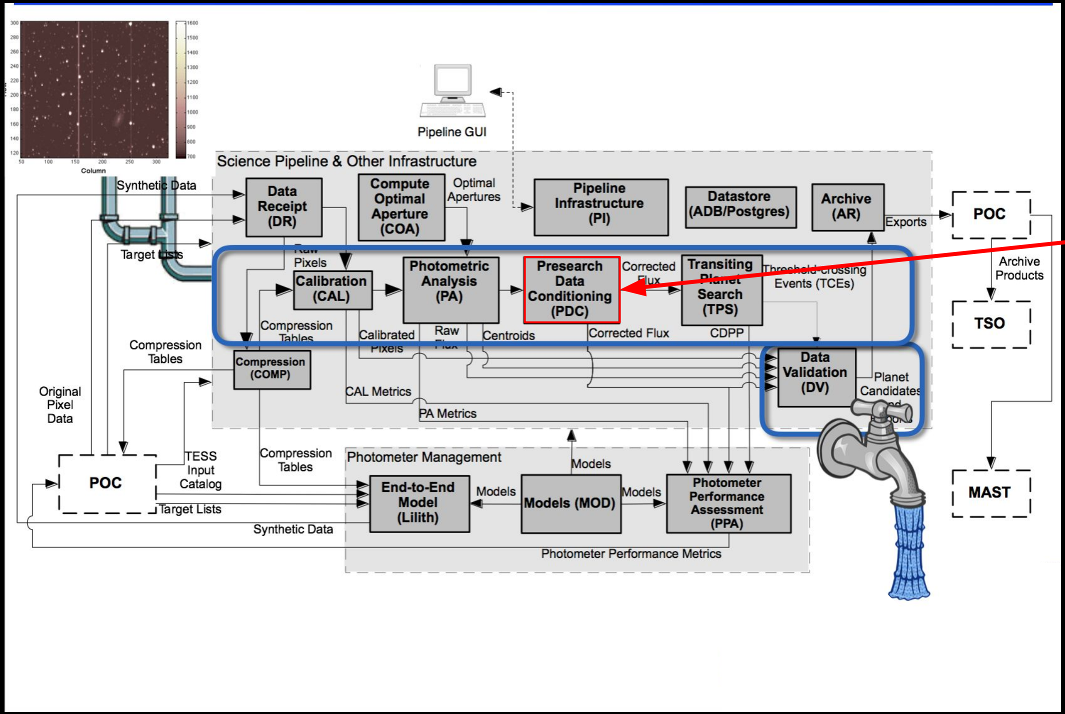

flux
0
1000
2000
3000
time [cadences]
C
fast oscillation
flux

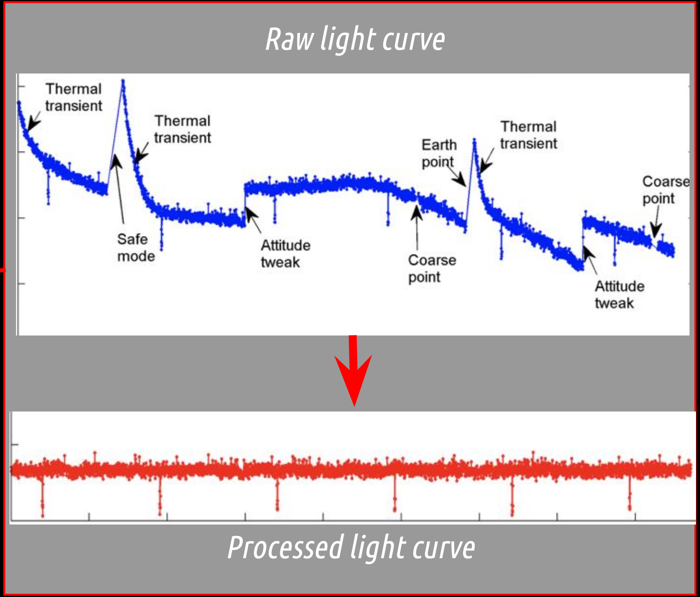

"Global" lightcurve view
Flux
Flux errors
Centroids
"Local" lightcurve view
Flux
Flux errors
Centroids

The data: real light curves



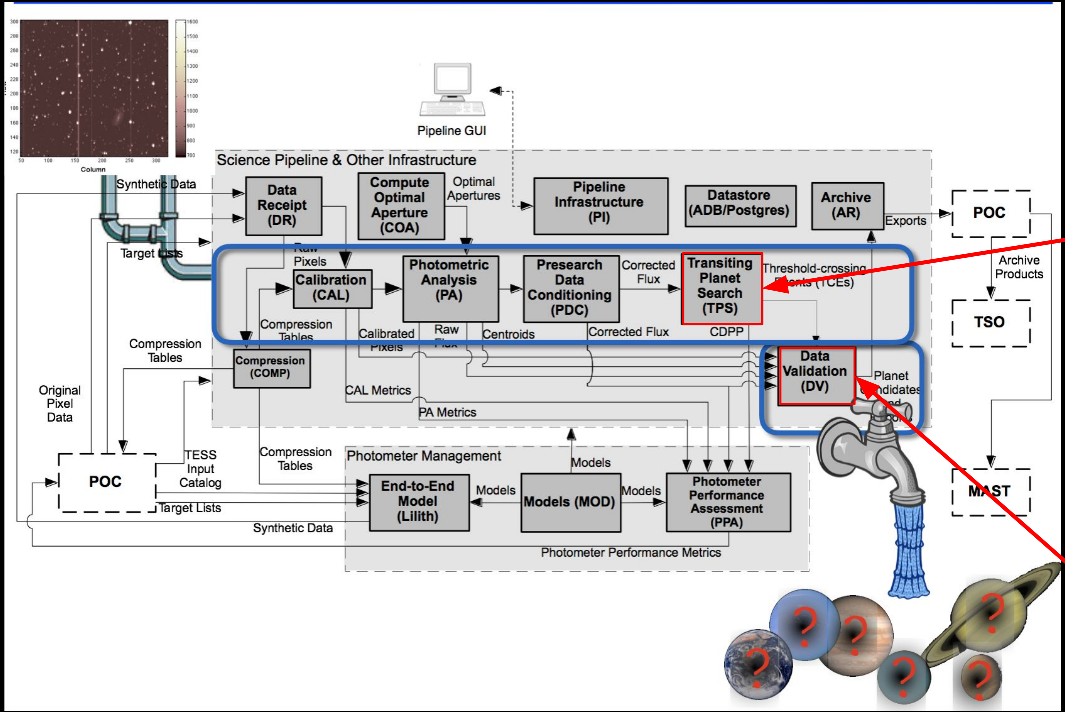
The data: detrended light curves

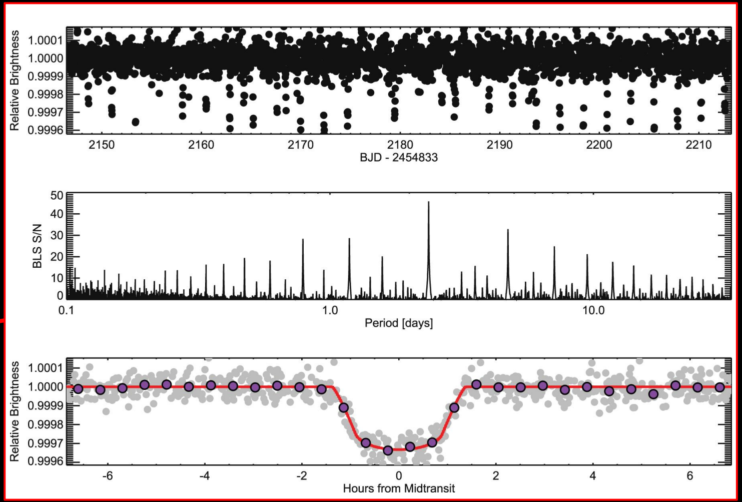




- Remove trends present on all stars to leave only astrophysical signal

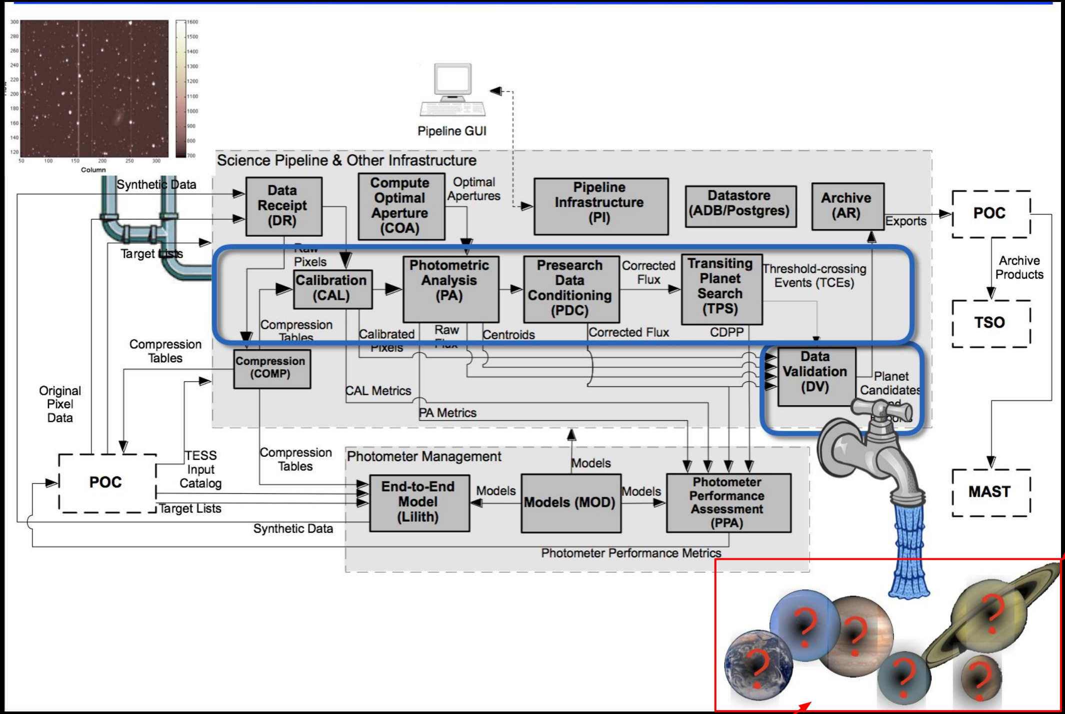
The data: Transiting Planet Search





- Search for transiting planets in frequency domain.
- Strong candidates are analysed using statistical tests (DV)

The data: planet candidates



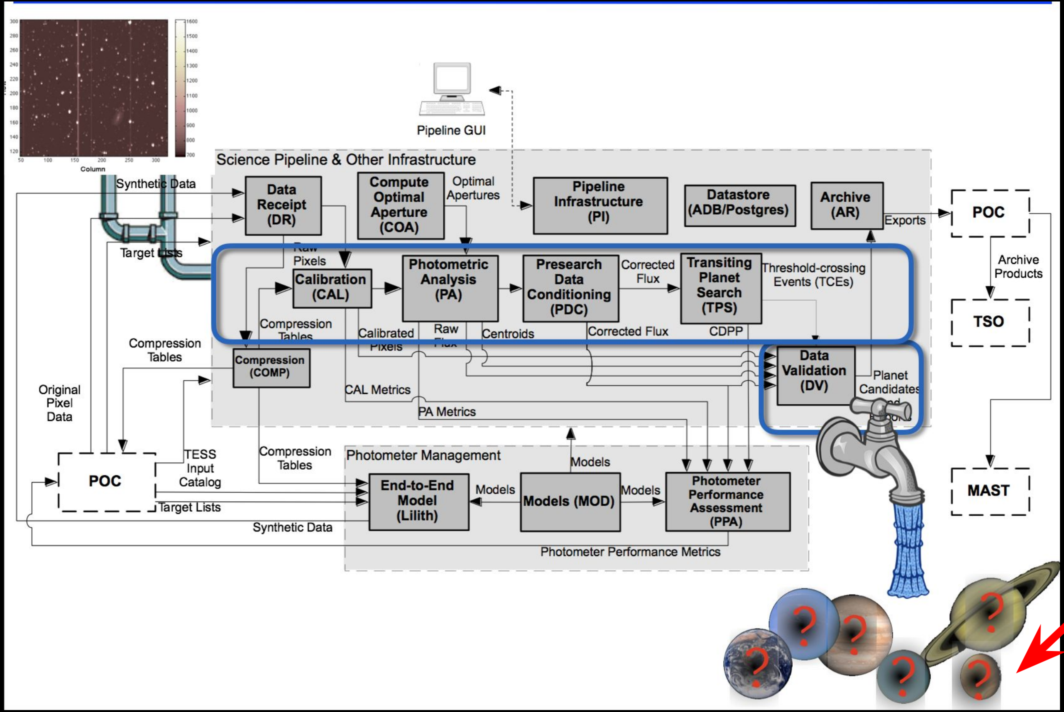
Planet candidates (TCEs) are analysed to determine which are planets.

Often performed:

- By human vetters
- Using classical statistical techniques
- Using Machine Learning

...Could we start from this point?

Incremental: Classify planet candidates detected by the pipeline



Classify candidates detected by TESS pipeline

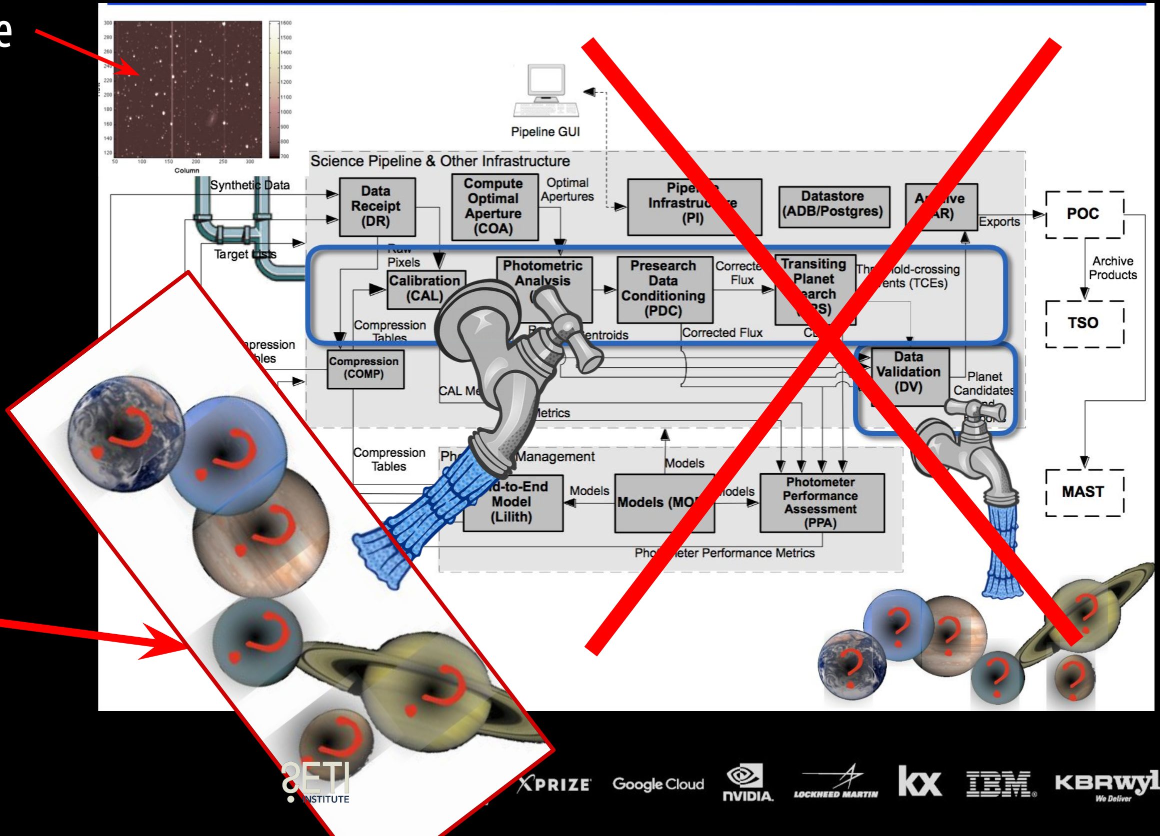
Planet, EB, BEB?

Innovative approach: Classifying directly from pixel data

Target Pixel File

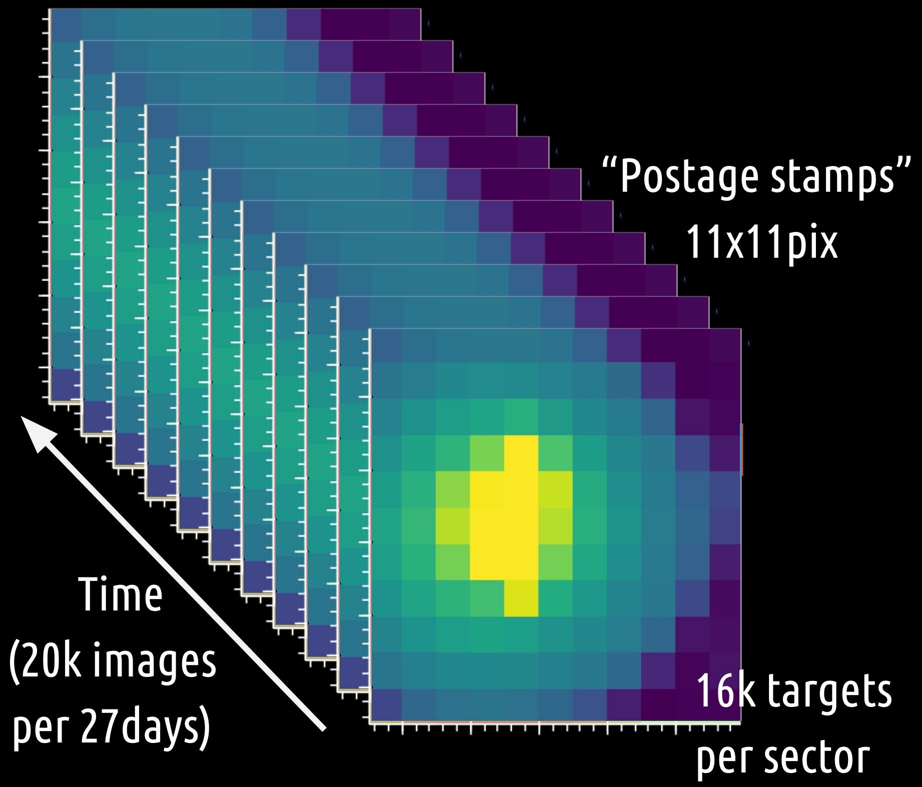
Cut out the pipeline entirely

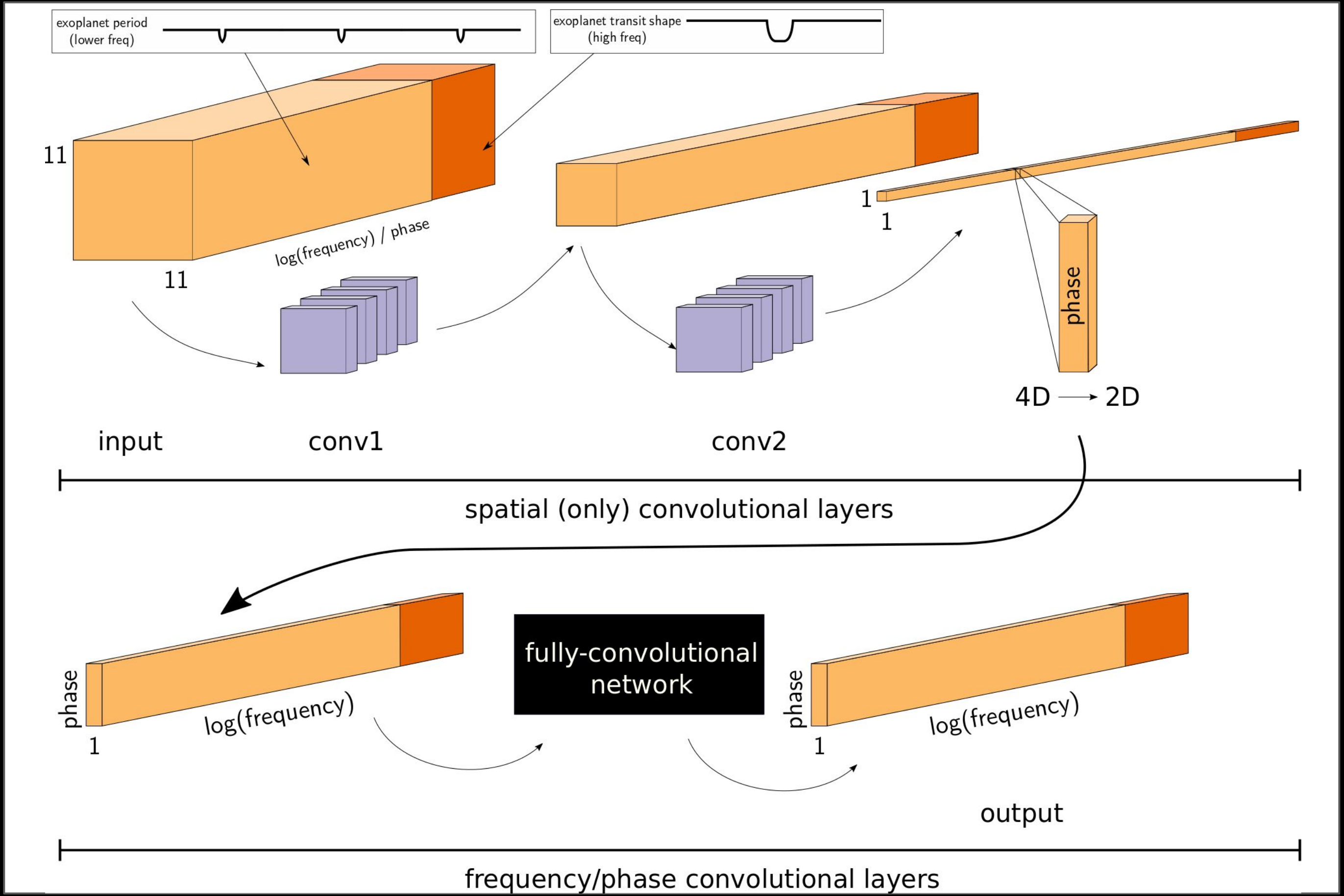
Planet, EB, BEB?



Innovative approach: Classifying directly from pixel data

- Train a Convolutional Neural Network (CNN) directly on pixels
- Transform image to more appropriate representation, i.e. frequency domain for periodic data
- Incorporate our domain knowledge into the network architecture and learning algorithm, rather than the data




exoplanet period
(lower freq)
exoplanet transit shape
(high freq)
11
11
log(frequency) / phase
1
1
phase
4D → 2D
input
conv1
conv2
spatial (only) convolutional layers
phase
1
log(frequency)
fully-convolutional network
phase
1
log(frequency)
output
frequency/phase convolutional layers

Next steps...

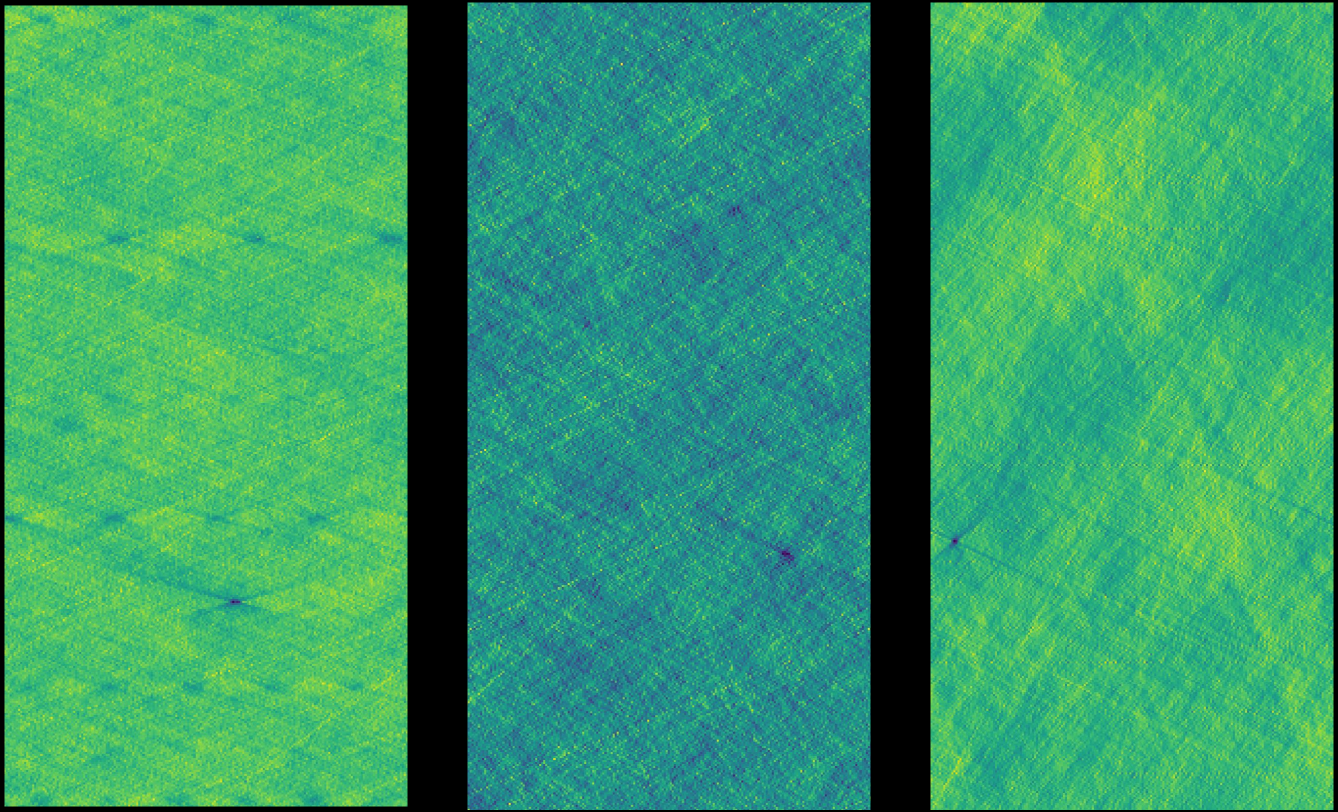
Week 3:

- *Avenue 1*: Re-produce Shallue & Vanderburg 2017 results
- *Avenue 2*: Setup data infrastructure/get basic CNN training

Week 4:

- *Avenue 1*: Incorporate new domain knowledge
- *Avenue 2*: Iterate on model/implement data balancing methods

Planets



No planets