### **Machine Learning Applications in Astronomy**

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## Machine Learning (ML) for Astronomy

- Enabling Science
- Transient Science
- Catalog Science
- New Techniques
- Supporting ML in Astronomy

## JPL ML-Astronomy Collaborations

**Current and Past** 

- Palomar Transient Factory, intermediate Palomar Transient Factory, Zwicky Transient Facility
- The Very Long Baseline Array (VLBA) Fast Radio Transients Experiment (V-FASTR)
- Variables and Slow Transients (VAST) survey, part of Australian Square Kilometre Array Pathfinder (ASKAP)
- RealFast project at the Very Large Array (VLA) radio telescope
- MIT Lincoln Lab collaboration on Space Surveillance Telescope (SST) data
- Dark Energy Survey

# **Enabling Science**

## Big Telescopes, Big Science, Big Data



Large Synoptic Sky Telescope (LSST) 15 TB/night



Wide-field Infrared Survey Telescope (WFIRST)





Square Kilometre Array 160 TB/second

James Webb Space Telescope (JWST)

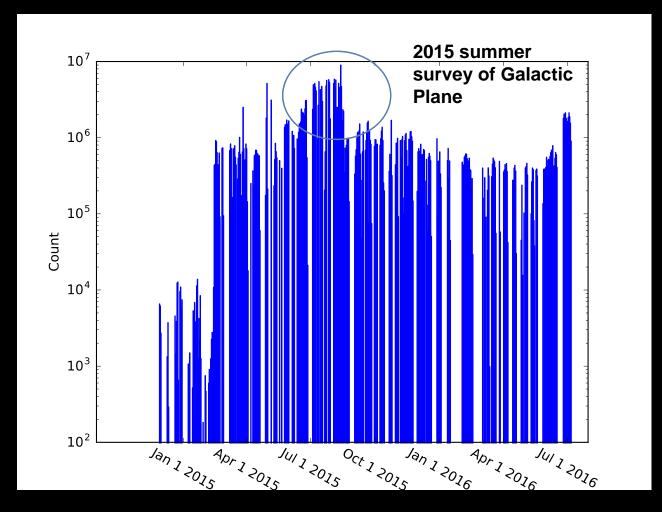
**S**S

Transiting Exoplanet Survey Satellite (TESS)

11/01/17

## Millions of Detections per Night...in 2015

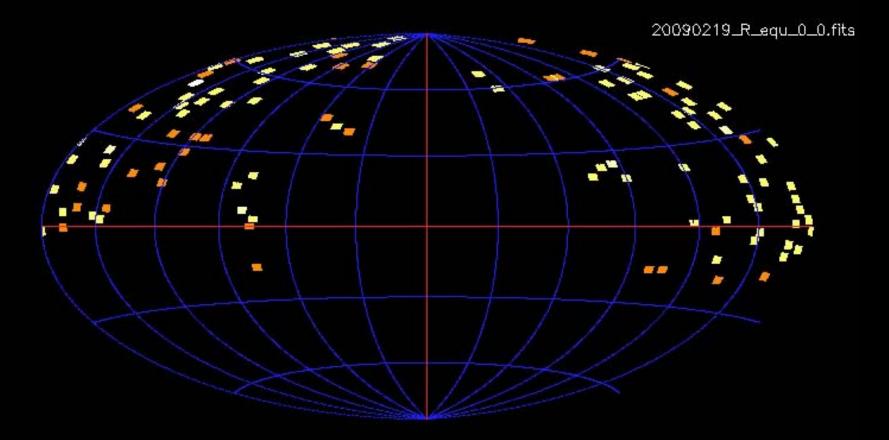
intermediate Palomar Transient Factory 2015-16



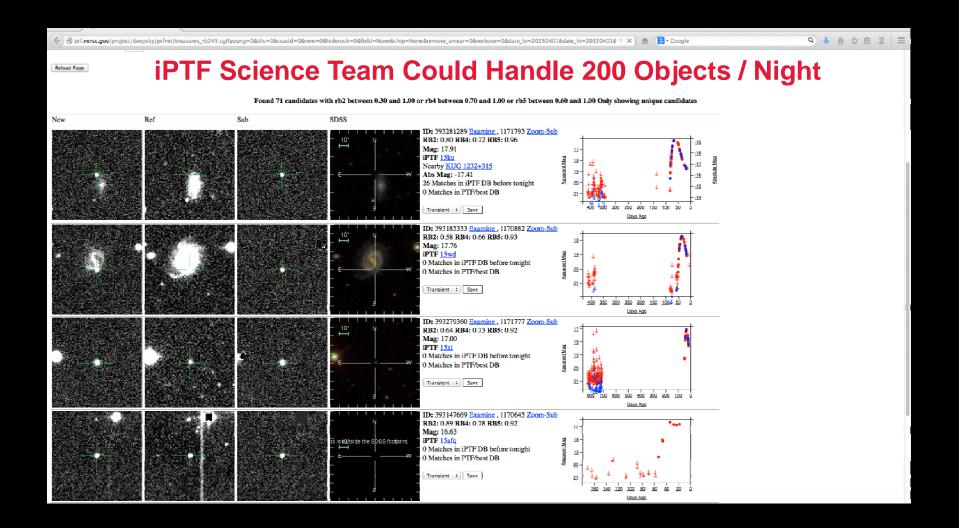
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## **Huge Catalogs from All-Sky Surveys**

Observations of millions of objects, including spectra and lightcurves

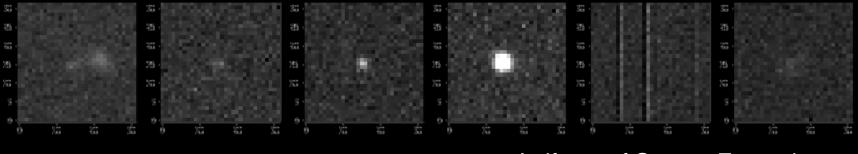


### **Science Team Size is Constraining Factor**

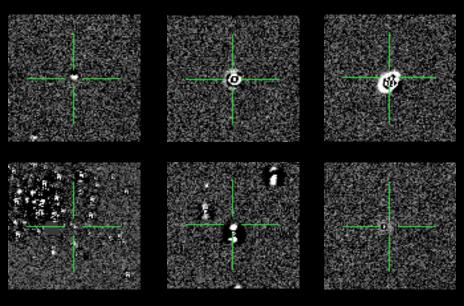


### Machine Learning Classifiers Filter False Detections

Are these candidates optical or pipeline artifacts?



Artifacts of Source Extraction



Artifacts of Image Differencing

## **Transient Science**

### **Astronomical Transients**

• Explosive events, very short duration

Gamma Ray Burst (milliseconds to hours)



Supernova (weeks to months)



Transience from our observational perspective



Planetary transit

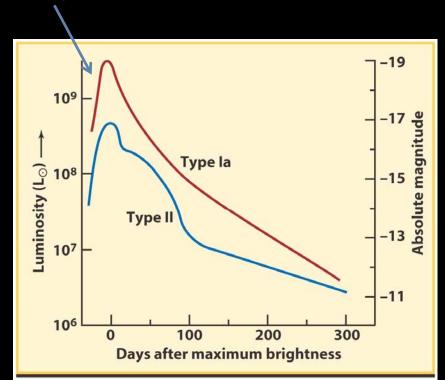


### Asteroid

### **Transient Science Requires Real-time Algorithms**

- Find all scientificallyinteresting observations
- Filter all irrelevant observations
- Goal: trigger follow-up of science-rich targets

Ideally, find it here

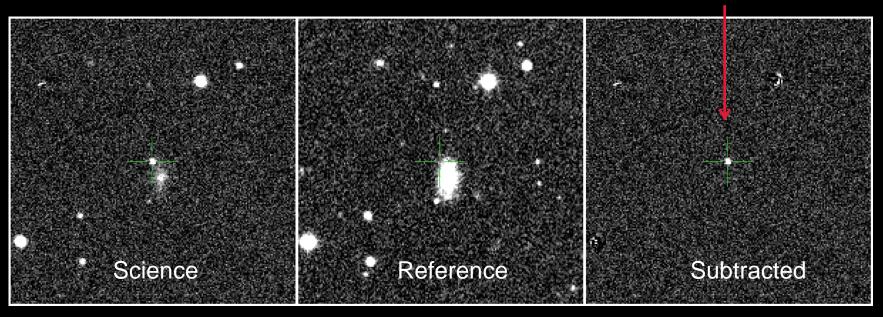


### **Real-time Filtering**

Optical Astronomy Example from iPTF

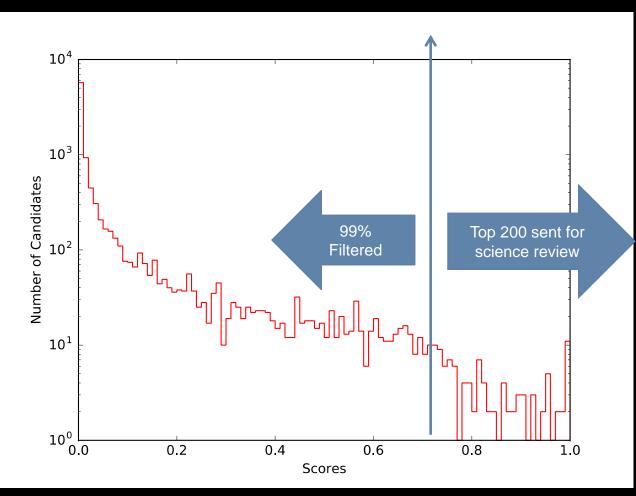
 Automated classifier scores candidates from 0 (bogus) to 1 (real)

Is this candidate real or bogus?



### **Real-time Filtering**

### Optical Astronomy Example from iPTF

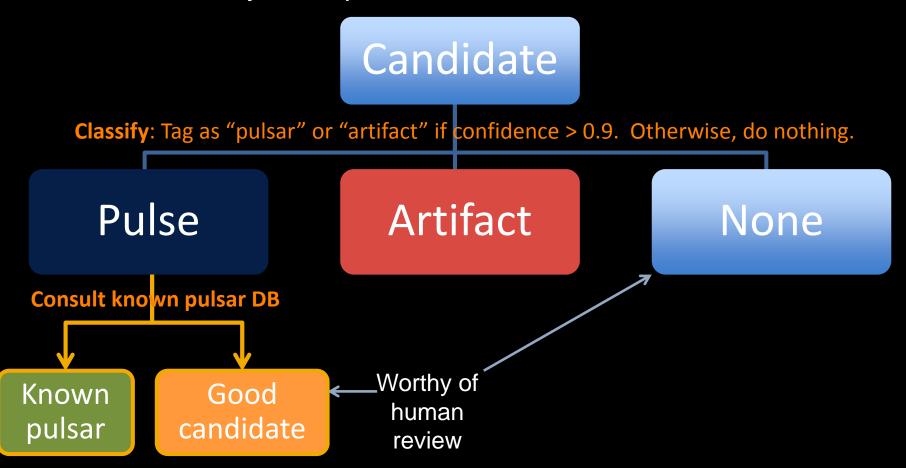


#### Set decision threshold that filters 99%

NASA / Caltech / JPL / Instrument Software and Science Data Systems

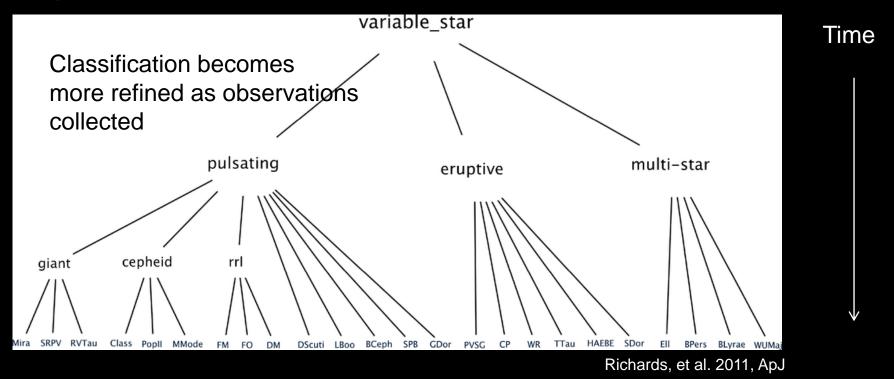
## **Real-time Filtering**

Radio Astronomy Example from V-FASTR / VLBA



### **Real-time Classification**

 Modern "data brokers" perform real-time classification of objects



 Science users contribute filters to downselect the information they want

# Catalog Science

### **ML** Applications

- Stellar classification
- Star / galaxy separation
- Identification of planetary transits (exoplanets)
- NEO identification / tracking
- Estimating cosmological parameters

## **Mining Astronomical Archives**

Weak Lensing Archives

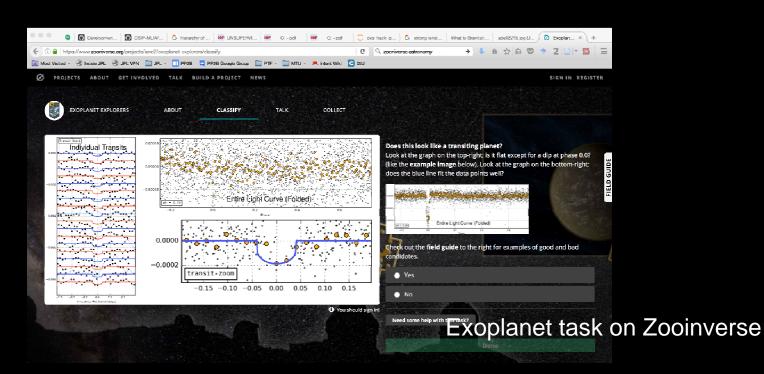
Circular distortion patterns created by strong lensing

Machine learning task of outlier detection can help constrain the examples used for calculating parameters for weak gravitational lensing.

## New Techniques

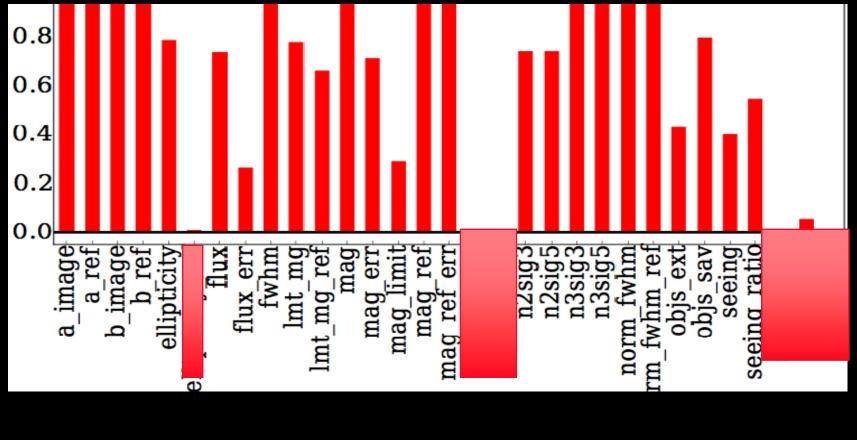
### **Crowdsourcing + ML**

- Crowdsourcing platforms offer interfaces that integrate with ML algorithms and build training data quickly
- Allow interaction with scientists, general public



## Responding to Instrument and Survey Changes

• Example of how a pipeline upgrade changed data characteristics at iPTF

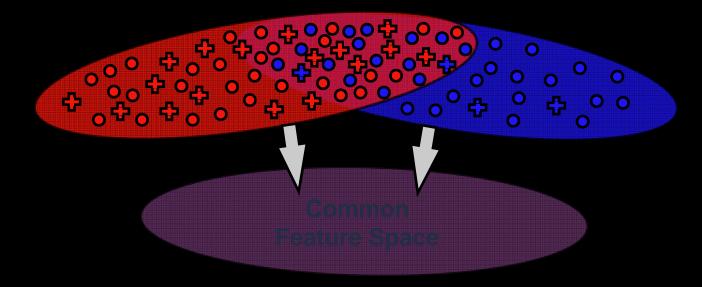


### **Domain Adaptation**

- Computes mapping between source and target data sources that share common science goals
- Continuous data record between old and new missions

**Old Instrument, pre-upgrade** 

New Instrument, post-upgrade



### **Deep Learning**

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Pixel values, SIFT, HoG, histograms of visual word

> DFT, wavelets, time series statistics

Bag of Words TFIDF				
TFIDE				
Z				
, 7				
of visual words				

### **Deep Learning**

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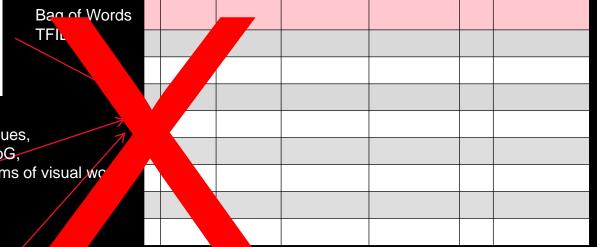
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Pixel values, SIFT, HoG, histograms of visual wo

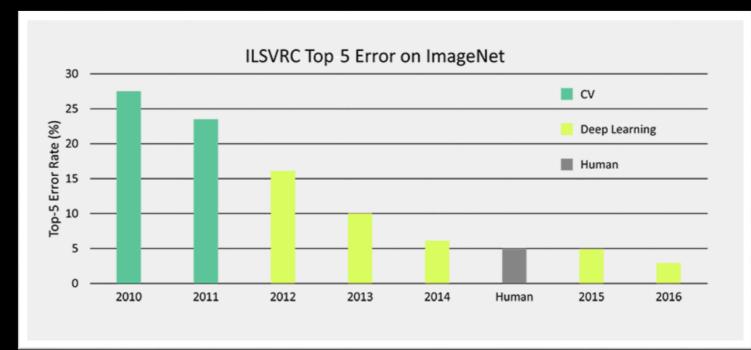
> DFT, wave!..., time series statistics

#### Does not require expert-engineered features



### **Deep Learning**

### ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



https://www.dsiac.org/resources/journals/dsiac/winter-2017-volume-4-number-1/real-time-situ-intelligent-video-analytics

# Supporting ML in Astronomy

## **Challenges and Opportunities**

### Programmatic

- Space telescope managers don't know we exist
- ML experts not involved in data pipeline requirements and design

#### Financial

- Few ROSES opportunities that support ML work in astronomy
- Limited or no budget for high level data products produced by ML

#### Cultural

- "It's just software."
- "My post-doc can do it."



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