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Leveraging Annotated Archival Data with Domain Adaptation to Improve Data Triage in Optical Astronomy

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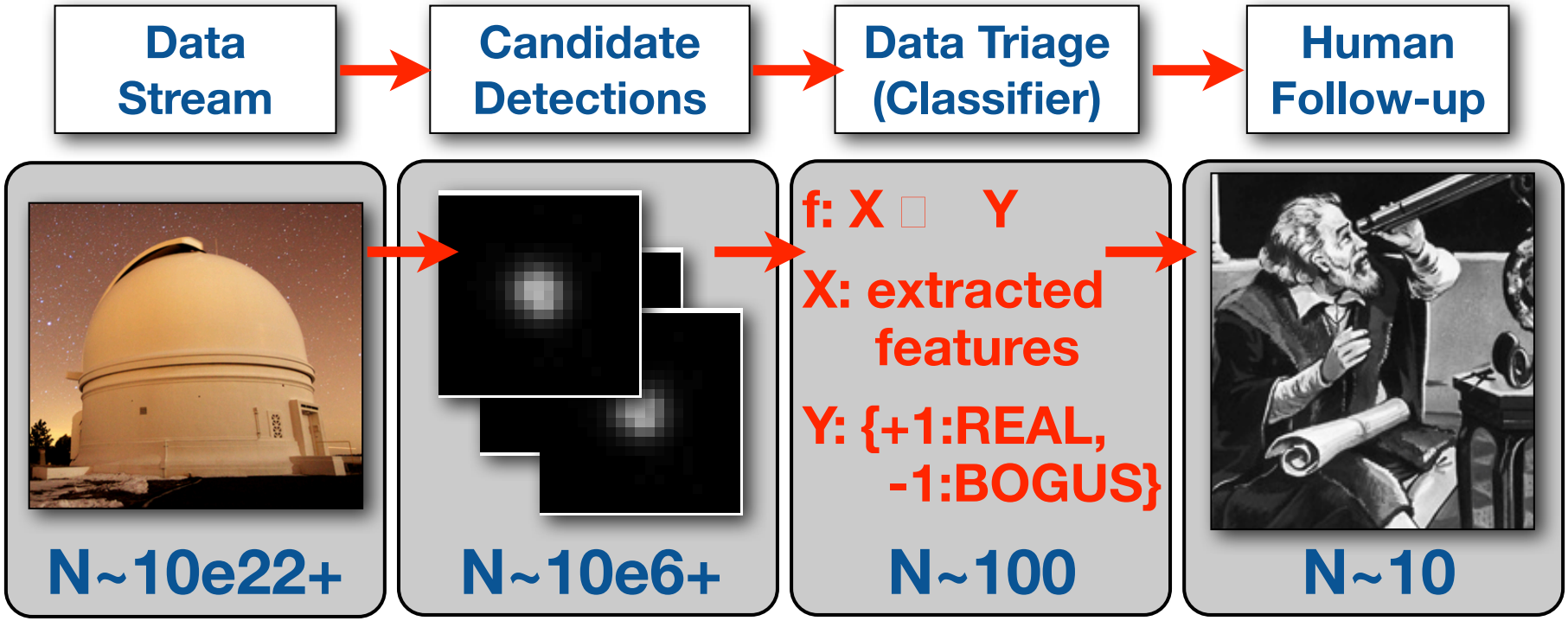
Automated Triage of Astronomical Data



Supervised Learning for Data Triage

Training Data (labeled)

$$(X,Y)^{\text{train}} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$$
$$\mathbf{x}_i \in \mathbb{R}^n \text{ (features)}$$
$$y_i \in \{\text{real}, \text{bogus}\}$$

Test Data (unlabeled)

$$(X,Y)^{\text{test}} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{M}$$
$$\mathbf{x}_i \in \mathbb{R}^n$$
$$y_i \text{ unknown}$$

Trained Classifier

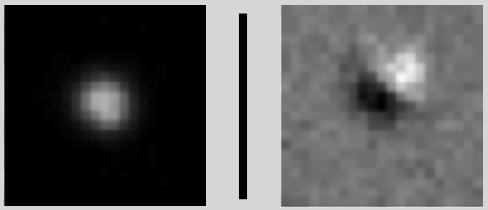
$$f(\mathbf{x}) \rightarrow y$$

Test Predictions

$$\{y_i\}_{i=1}^{M}$$

Follow-up

Real



Bogus

Assumption: $(X, Y)^{\text{train}}$, $(X, Y)^{\text{test}}$ drawn i.i.d. *from the same distribution* $\mathcal{P}(X, Y)$

Violated when measurement conditions change

- Due to: sensor modifications / changes to imaging pipeline

How can we use existing labeled data when such changes occur?

Applications

- Bootstrap detection systems for new surveys using old data
- Provide data continuity for ongoing surveys

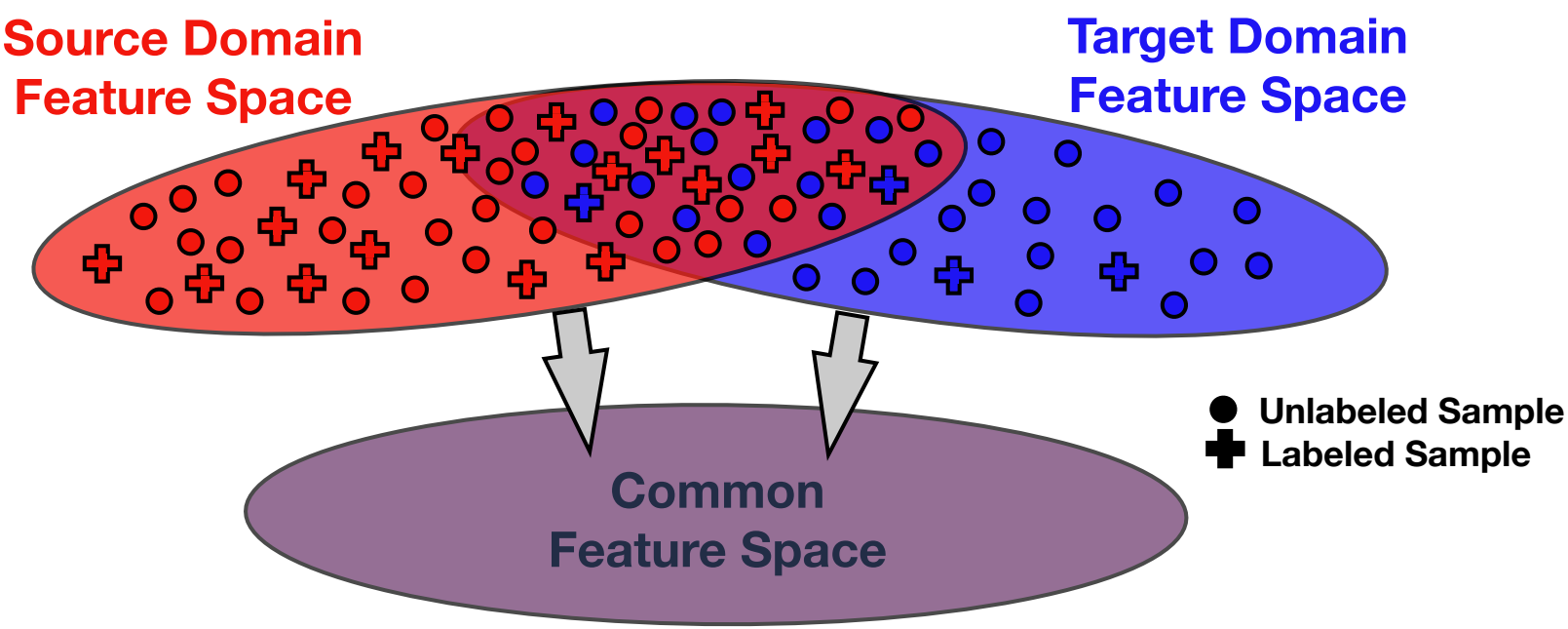
Domain Adaptation

Proposal: use **domain adaptation** to adapt data/classifiers from earlier surveys with similar science goals

Given: labeled **source** (training) samples $\mathcal{D}^S \sim \mathcal{P}^S(X, Y)$

(mostly) unlabeled **target** (test) samples $\mathcal{D}^T \sim \mathcal{P}^T(X, Y)$

Compute: mapping between source and target feature spaces

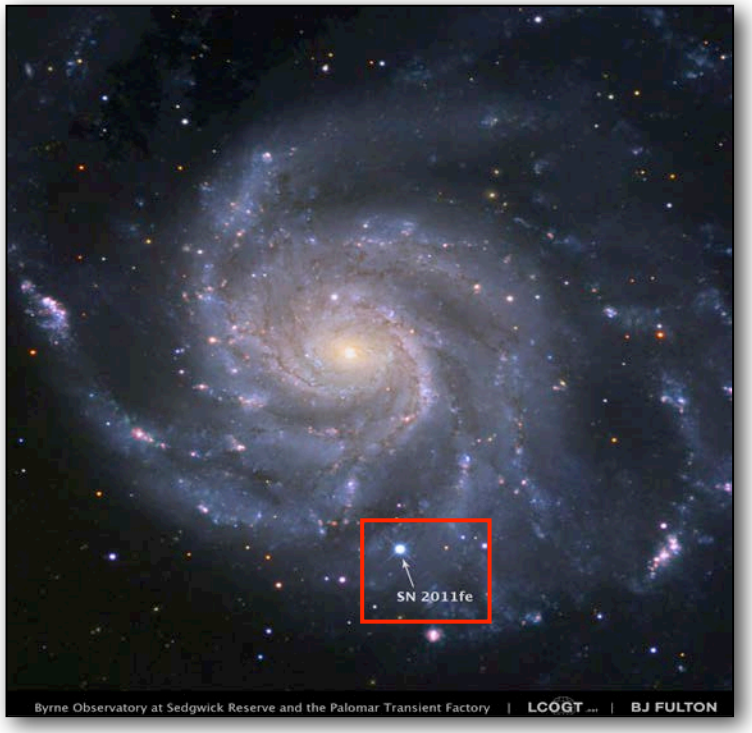


Case study: Transient Detection with the Intermediate Palomar Transient Factory (iPTF)

Fully-automated, wide-field optical transient survey

Focus on supernovae (short duration), variable stars (persistent)

iPTF succeeded Palomar Transient Factory (PTF) in January 2013



Palomar P48 + Large field camera captures 7.8 deg^2 on the sky

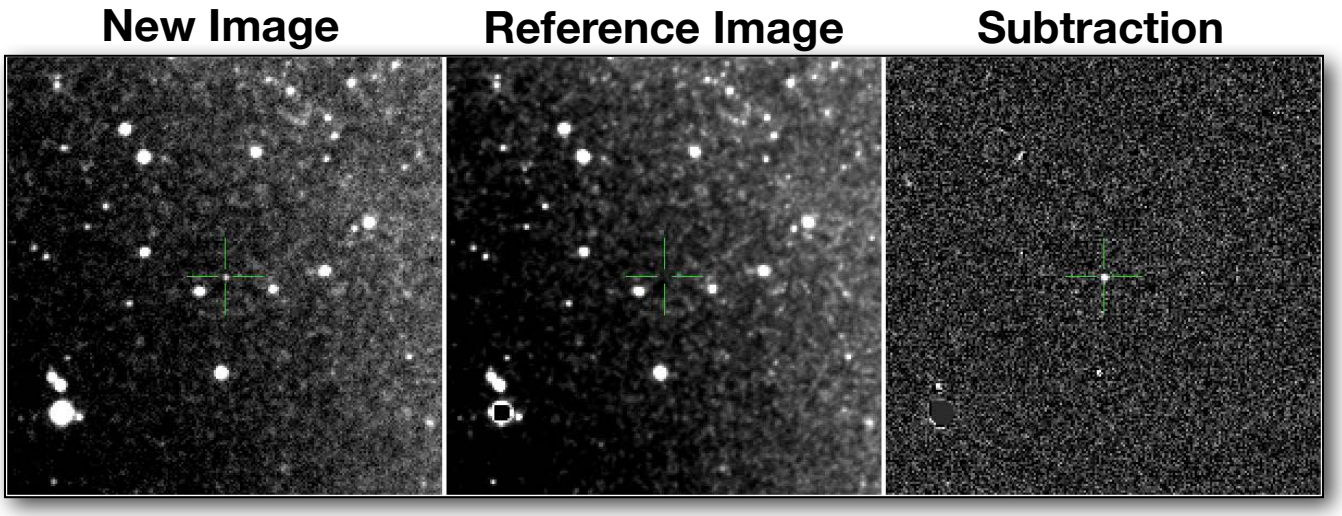
http://ptf.caltech.edu/iptf/

Detects 500K – 1M candidate sources per night

≈0.1% of all point source detections real transients

iPTF Candidate Detection + Classification

Point source detection: via image subtraction pipeline

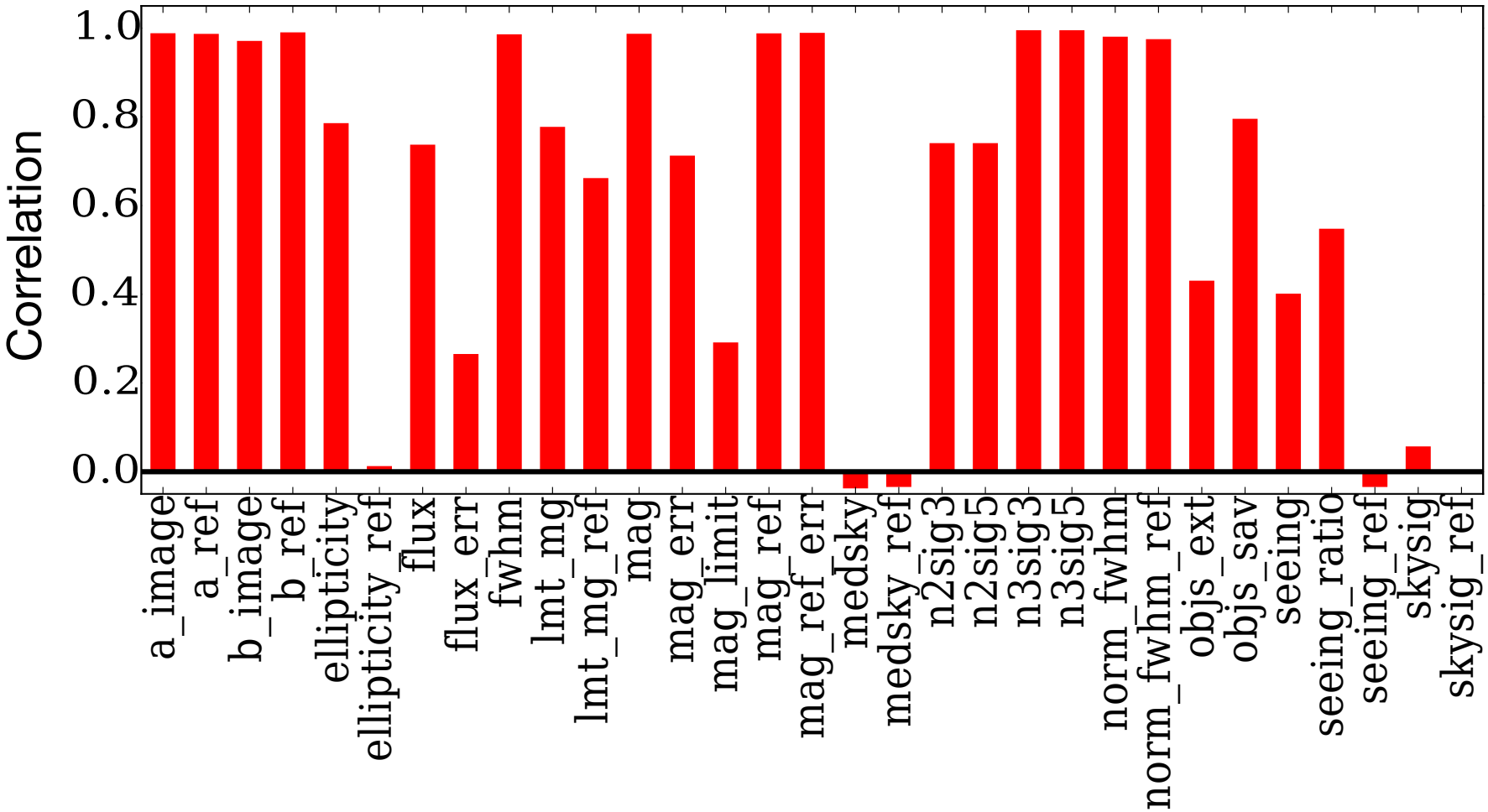


Real-Bogus classifier: (Bloom et al., 2011; Brink et al., 2012)

- Classifies point source detections; prioritizes high-confidence detections for human review/confirmation
- **Trained using PTF data**
  ⇒ iPTF upgrade changed image processing pipeline

  ⇒ **produced suboptimal predictions on new iPTF data**

Feature drift due to iPTF pipeline upgrade



Correlation between PTF and iPTF features for real (spectroscopically-verified) transient sources

Experiment: PTF → iPTF Transient Detection

Goal: adapt PTF-trained classifier to iPTF domain

Proof of concept for future surveys

- PTF/iPTF → Zwicky Transient Facility (ZTF, 2017)

Validation Data

- **PTF:** 37,028 verified reals, 39,613 bogus
- **iPTF:** 18,433 verified reals, 19,000 bogus

Features (31 total)

- candidate: mag, mag_err, flux, flux_err, a_image, b_image, fwhm, mag_ref, mag_ref_err, a_ref, b_ref, n2sig3, n3sig3, n2sig5, n3sig5
- subtraction: objs_extracted, objs_saved, lmt_mg_new, lmt_mg_ref, medsky_new, medsky_ref, seeing_new, seeing_ref, skysig_new, skysig_ref
- misc: mag_from_limit, ellipticity, ellipticity_ref, normalized_fwhm, normalized_fwhm_ref, seeing_ratio

PTF → iPTF Algorithm Comparison

Geodesic Flow Kernel (GFK, Gong et al., CVPR12)

- Computes domain-invariant features from intermediate subspaces "between" source & target domains
- Unsupervised: requires no labeled target data

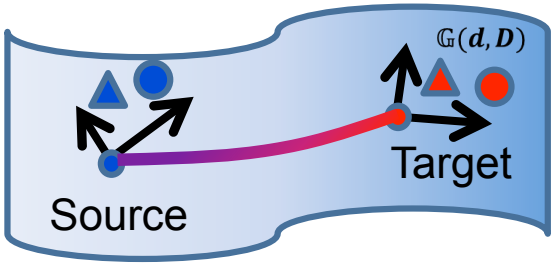


Figure credit: Gong et al., 2012

Co-Training for Domain Adaptation (CODA, Chen et al., NIPS11)

- Partitions feature space, trains a classifier for each partition
- Adds high-confidence predictions on target data to training set
- Learns informative features across domains

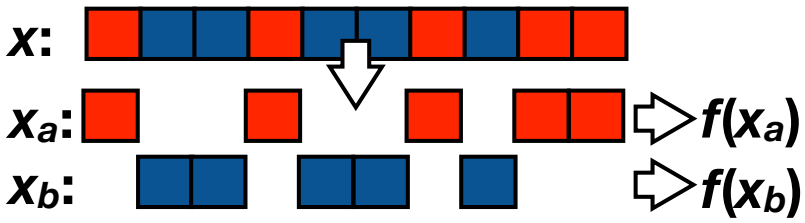
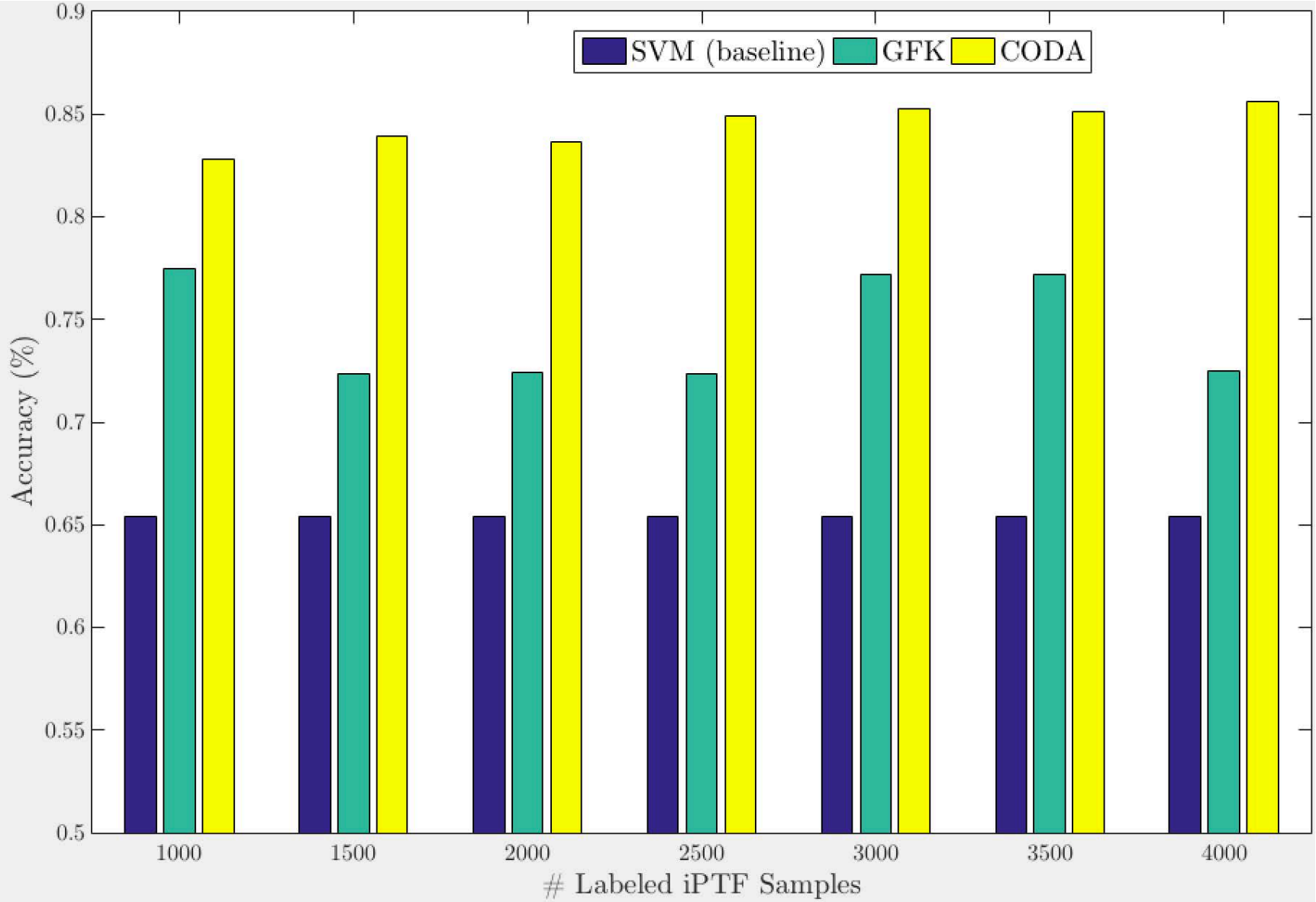


Figure credit: Chen et al., 2011

PTF → iPTF Prediction Accuracy



Bue et al., Domain Adaptation / Data Triage / Optical Astronomy

Summary

- Automated transient detection accuracy suffers when training/test distributions differ
- Domain adaptation can help
  - GFK and CODA show 5-20% improvements in accuracy over baseline

Ongoing/future work

- Diagnose iPTF image processing pipeline artifacts
- Use PTF/iPTF data to bootstrap Real-Bogus classifier for Zwicky Transient Facility

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