

A Convolutional Autoencoder-Based Pipeline for Anomaly Detection and Classification of Periodic Variables

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Processing Systems
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1. The Chinese University of Hong Kong
2. Center for Computational Astrophysics, Flatiron Institute
3. The Pennsylvania State University





Introduction And Motivation

Image credit: Nasa.gov

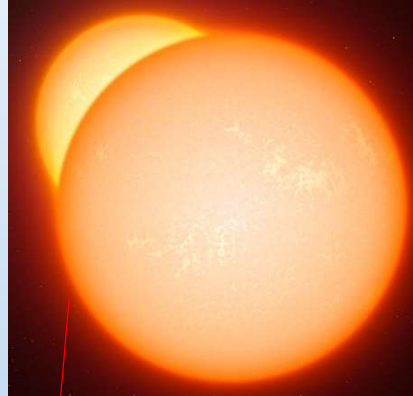
Searching For Anomalous Periodic Variable Stars

Image credit: astro.wisc.edu



Intrinsic

Image credit: newatlas.com

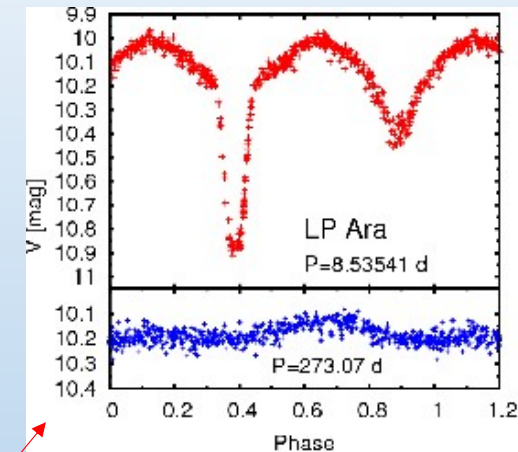


Extrinsic

Or



Image credit: Michalska et al. (2009)



- Periodic variable stars → brightness changes periodically
- Source: Pulsations, eclipsing, and more ...
- Physics of sources **encoded in their light curves**
- Search for wild cats → **New discoveries**



Methodology

Image credit: Nasa.gov

Data Pre-Processing

The Zwicky Transient Facility Catalog of Periodic Variable Stars

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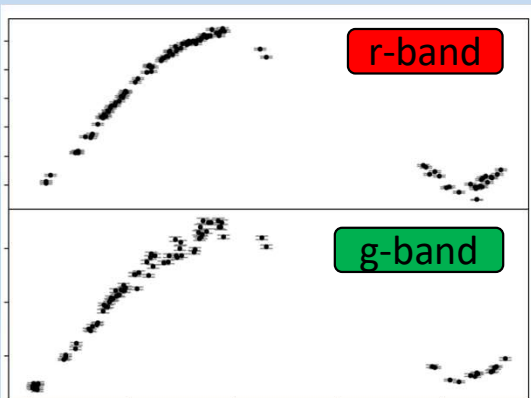
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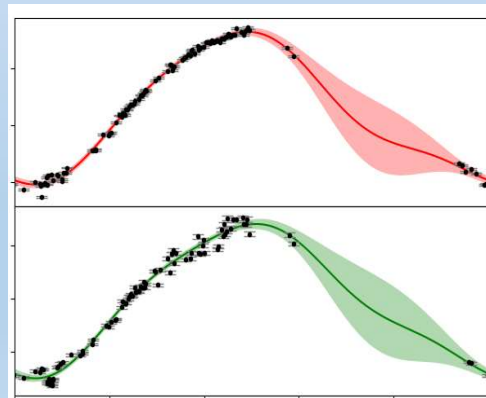
⁶CAS Key Laboratory of Space Astronomy and Technology, National Astronomical Observatories, Chinese Academy of Sciences, Beijing 100101, People's Republic of China

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Raw Detections



Multivariate-GPR



Phase-Folding

Image credit: wordpress.com

| | | | | | | | | | |
|---|---|---|---|----|----|----|----|----|----|
| 1 | 3 | 5 | 7 | 9 | 11 | 13 | 15 | 17 | 19 |
| 2 | 4 | 6 | 8 | 10 | 12 | 14 | 16 | 18 | 20 |

Stacked "Images"

Latent Features Extractions

| | | | | | | | | | |
|---|---|---|---|----|----|----|----|----|----|
| 1 | 3 | 5 | 7 | 9 | 11 | 13 | 15 | 17 | 19 |
| 2 | 4 | 6 | 8 | 10 | 12 | 14 | 16 | 18 | 20 |

Stacked "Images"

© Machine Learning @ Berkeley

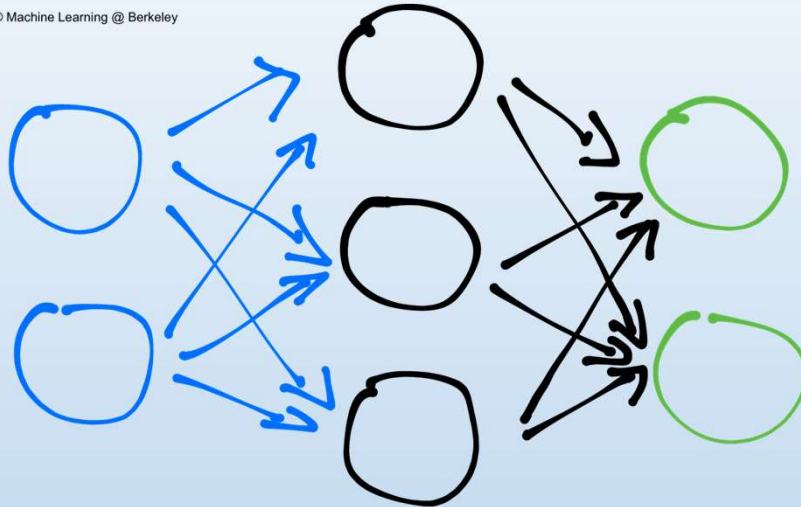
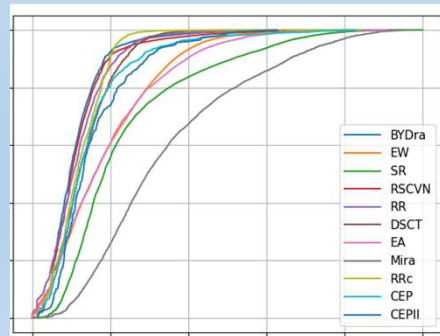


Image credit: UC Berkeley

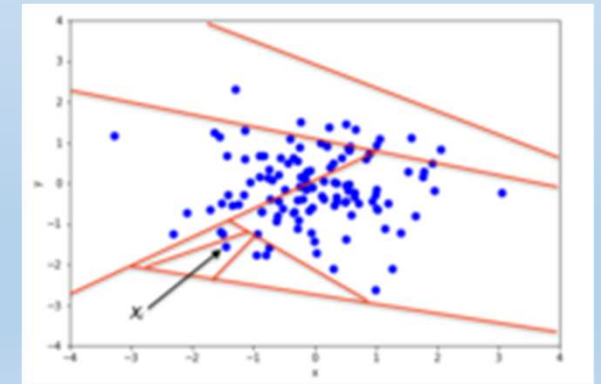
Convolutional AutoEncoder



List of Anomalies

Latent Features

Image credit: Wikipedia.com



Isolation Forest

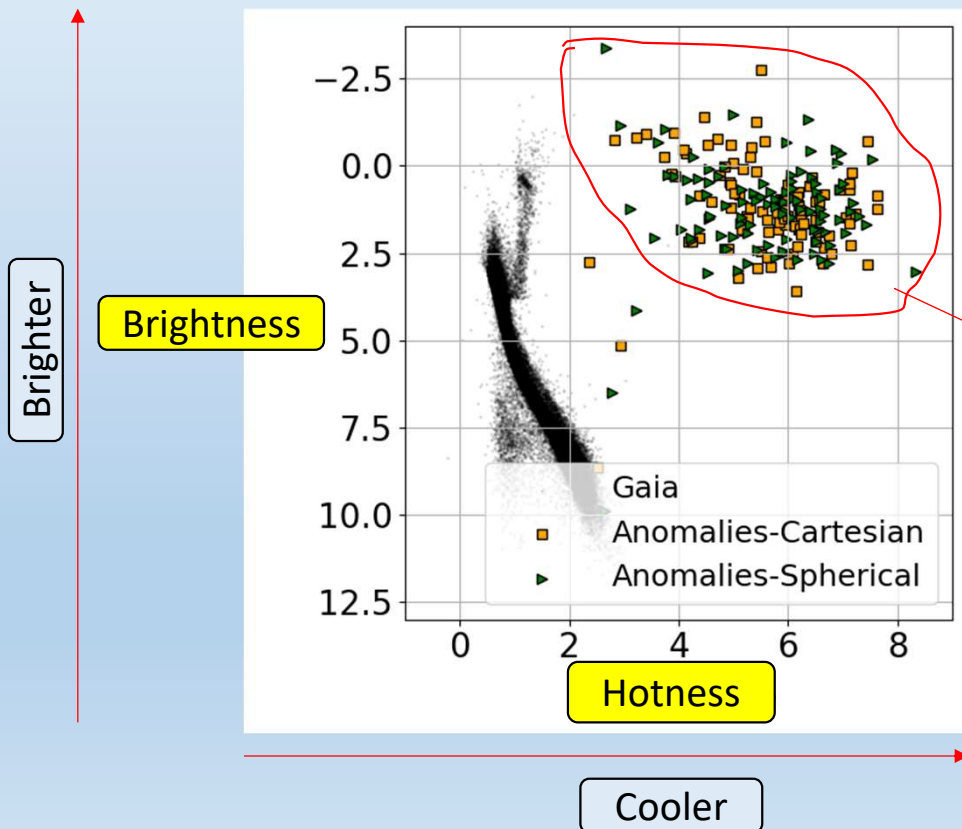


Results

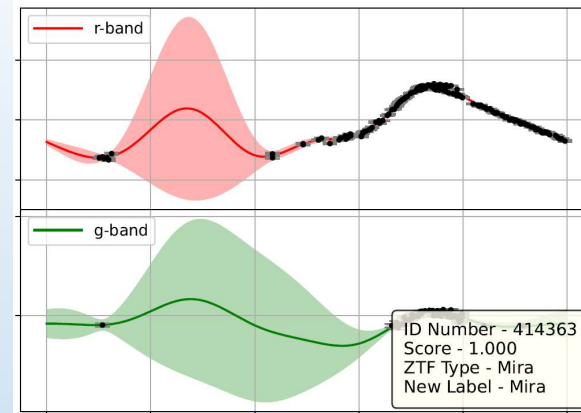
Image credit: Nasa.gov

The Anomalies

- Anomalous periodic variables are
 - Irregular oscillating
 - High variability



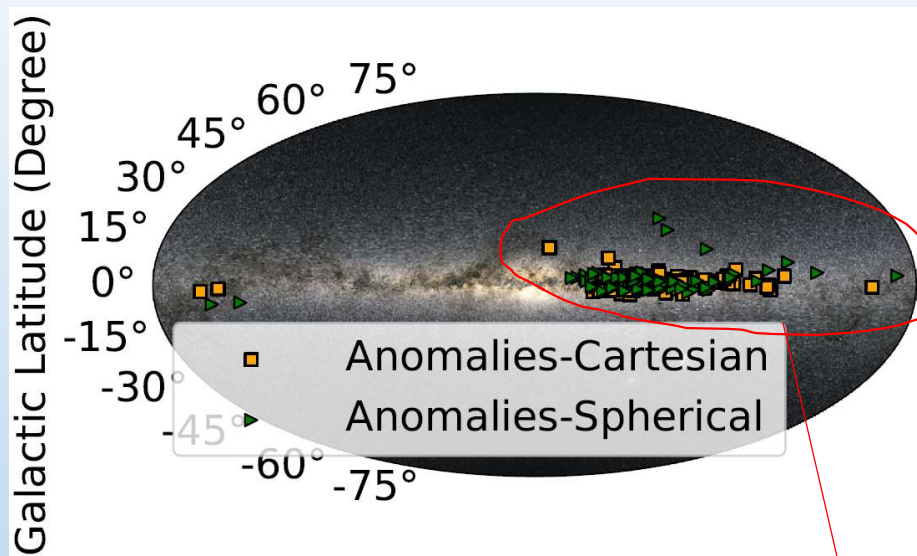
Illustrations



- Plotted HR-Diagram
- Anomalies are
 - Brighter
 - Cooler
- Corresponds to evolved stars In their late phase of evolution



The Anomalies



- Located in the vicinity of the Galactic disk
- Younger (with respect to the Galactic age)

LSST



Image credit: symmetrymagazine.org

Detailed Spectroscopic Follow-Up Is Strongly Recommended!

Classifications Using The SIMBAD Labels



Crossmatch

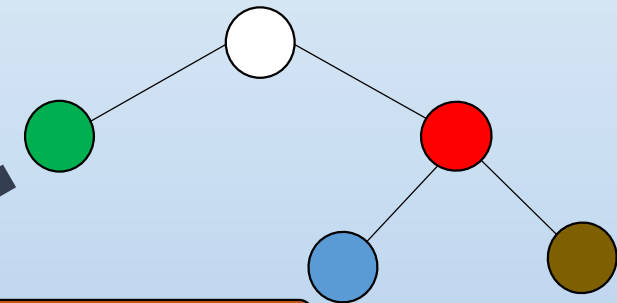


Labels

Latent Features



Hierarchical Random Forest



Confusion Matrix

- Good accuracy for SOME classes

| True label | C-Type | HB | RGB | S-Type | Voth | YSOL |
|-----------------|--------|-------|-------|--------|-------|-------|
| C-Type | 55.6% | 9.6% | 1.9% | 5.0% | 11.9% | 16.1% |
| HB | 0.0% | 74.1% | 0.0% | 3.7% | 11.1% | 11.1% |
| RGB | 6.7% | 0.0% | 80.0% | 0.0% | 6.7% | 6.7% |
| S-Type | 35.5% | 3.2% | 6.5% | 38.7% | 9.7% | 6.5% |
| Voth | 11.4% | 5.9% | 3.0% | 3.0% | 59.9% | 16.9% |
| YSOL | 11.4% | 10.3% | 1.6% | 2.7% | 37.5% | 36.4% |
| Predicted label | C-Type | HB | RGB | S-Type | Voth | YSOL |

| True label | AGNL | CEP | EB | LPV | Mira | Pec | Puloth | RR |
|-----------------|-------|-------|-------|-------|-------|-------|--------|-------|
| AGNL | 92.6% | 0.0% | 0.7% | 0.7% | 0.0% | 5.1% | 0.0% | 0.7% |
| CEP | 0.0% | 48.5% | 6.1% | 1.5% | 0.0% | 25.8% | 1.5% | 16.7% |
| EB | 0.1% | 0.2% | 92.0% | 0.4% | 0.1% | 4.7% | 0.4% | 2.1% |
| LPV | 1.1% | 0.0% | 16.7% | 51.7% | 5.1% | 21.2% | 0.6% | 3.7% |
| Mira | 0.5% | 0.0% | 19.9% | 5.0% | 46.3% | 24.9% | 0.5% | 3.0% |
| Pec | 1.2% | 1.3% | 16.7% | 8.8% | 2.2% | 62.4% | 1.2% | 6.2% |
| Puloth | 0.0% | 2.0% | 22.4% | 1.0% | 1.0% | 10.2% | 51.0% | 12.2% |
| RR | 0.0% | 0.0% | 4.4% | 0.3% | 0.2% | 2.7% | 0.1% | 92.3% |
| Predicted label | AGNL | CEP | EB | LPV | Mira | Pec | Puloth | RR |

Conclusion

I showed the application of machine learning in Astronomy for ...

1. Detecting anomalous periodic variable stars
2. Building classification model for periodic variable stars

Thank You

