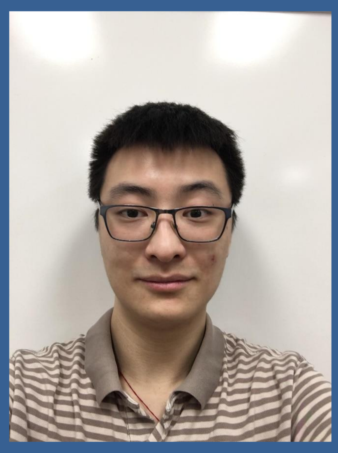
Exploring the X-ray Source Population in Globular Clusters with a Machine Learning Approach

Steven Chen[1], Hui Yang[2], Oleg Kargaltsev[1], Jeremy Hare[3]
[1]George Washington University, Washington, DC; [2]Institut de Recherche en Astrophysique & Planétologie, Toulouse, France; [3]Goddard Space Flight Center, Greenbelt, MD



Globular Clusters

- Around 150 globular clusters (GCs) are found in Milky Way (Kharchenko et al. 2013).
- >10 Gyrs old, masses range from ~10^5 to ~10^7 $M_\odot$
- X-ray sources detected in GCs include active binaries (ABs), Cataclysmic Variables (CVs), isolated or binary millisecond pulsars (MSPs), and low mass X-ray binaries (LMXBs).
- Only Chandra + HST observations have sufficient angular resolution to securely establish counterparts to X-ray sources in GCs, especially fainter ones.
- Great progress made in identifying X-ray sources in past two decades, constraining models of binary evolution, cluster dynamics, and compact object physics (Zhao & Heinke, 2022; Bahramian et al. 2020, etc.).
- However, 80% of ~2000 CXO sources in all Galactic GCs remain unclassified.
- Large number of sources, large number of source properties, and multiple possible counterparts and motivate machine learning (ML) classification approach.
- We present our training dataset of X-ray sources in GCs confidently classified in the literature, and classification results on the GC Omega Centauri (NGC 5139).

Omega Centauri (NGC 5139)

- Largest known galactic GC
- d=5.2 kpc, $M=4\times10^6 M_\odot$, age≈11.5 Gyr (Henleywillis et al. 2018)
- Hosts multiple stellar populations, suspected to have a dwarf galaxy origin
- Extensively observed by Chandra, classified sources include 1 qLMXB, CVs, recently discovered Spider MSPs (Henleywillis et al. 2018, Zhao & Heinke 2023)
- 75% CSC sources not classified!
- Recent HST catalog oMEGACat (Häberle et al. 2024)

Machine Learning Classification Pipeline (MUWCLASS)

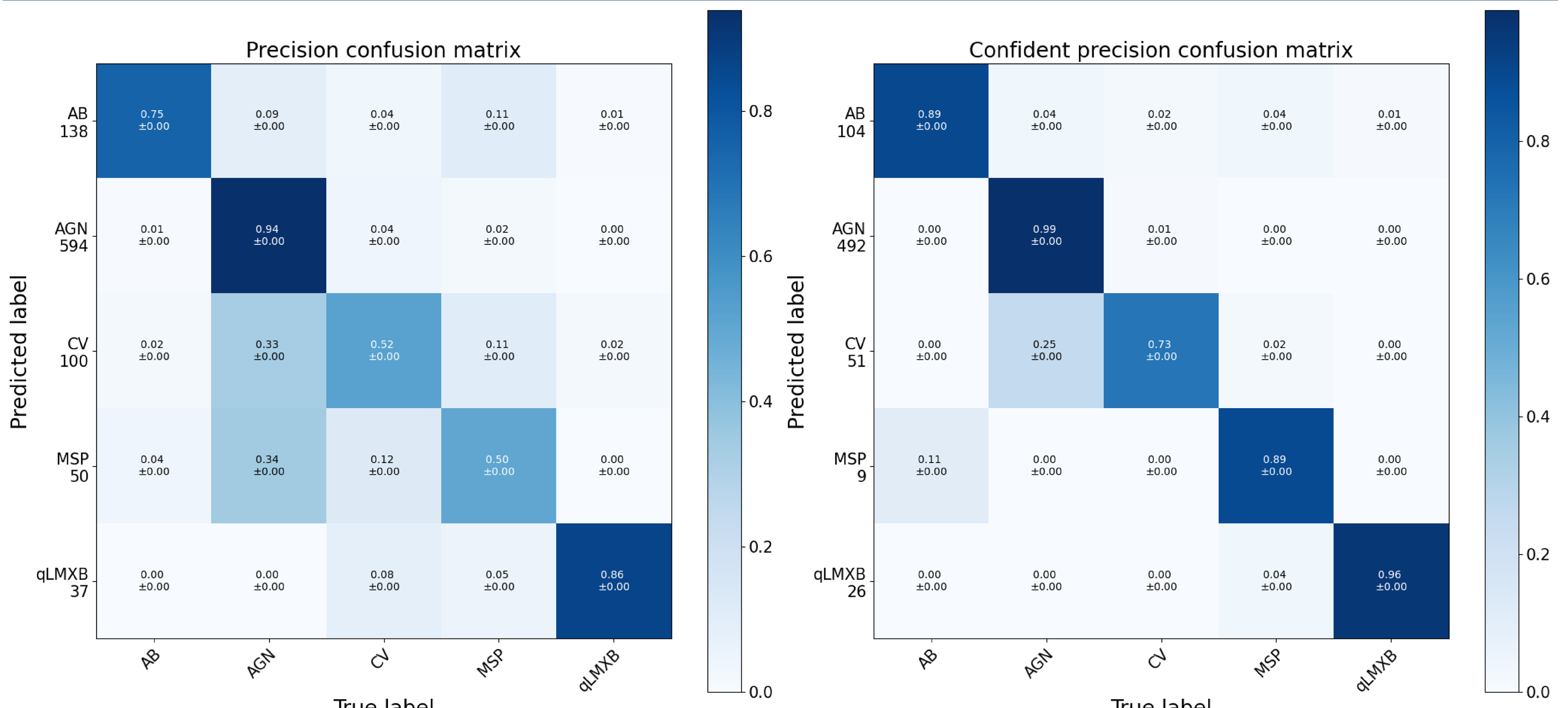
- MUWCLASS originally designed for classifying CXO sources in non-GC environments (Yang et al. 2022, 2024)
  - Random Forest Algorithm (scikit-learn)
  - Crossmatch to Gaia, 2MASS, WISE
  - Samples feature uncertainties
  - Account for various biases
  - Gives vector of probability that source belongs to each source class defined in training dataset (TD)
- Modified to use Chandra Source Catalog (CSC) 2.1, HST for classifying sources in GCs
- Probabilistic crossmatching using NWay (Salvato et al. 2018)
- Features: luminosities, absolute magnitudes, colors, CXO variability
  - GCs have known distances
- Use known extinction to GCs to deredden TD sources, and sources to be classified
- Classes: AB, AGN, CV, MSP, Spider-type MSP, LMXB
- Use upper limits to model cases where true counterpart is too faint to be detected
- To reduce bias, for each source to be classified, we implement following scheme:
  - If the source is missing a feature, remove the feature from pipeline
  - If the source is not missing the feature, remove TD sources that are missing that feature
  - Thus, classification is not influenced by what percent of TD sources of each class is missing feature

Training Dataset

- Compiled X-ray source positions and classifications from 50+ publications on GCs (Chen et al. 2023)
  - ~300 X-ray sources from 25 globular clusters
- Also compiled confident HST counterpart positions, magnitudes, when available in publications
- Crossmatched published X-ray coordinates to CSC
- Crossmatched published HST coordinates to HST UV Globular Cluster Survey (HUGS, Nardiello et al 2018), oMEGACat, and various CDF surveys
- Sources in these catalogs more uniformly processed than in literature, and astrometrically tied to Gaia
- ~150 confident crossmatches to HST
- 606 AGNs taken from Chandra Deep Fields, crossmatched to GOODS, CANDELS, HDUV surveys
- Summary of sources per class in all GCs and in Omega Cen only, with percent of sources with identified counterparts shown below

Class	Total	Counterpart %	Omega Cen	Counterpart %
MSP	62	24	7	0
CV	88	82	6	100
AB	111	100	1	100
qLMXB	37	30	1	100
AGN	621	57	6	100

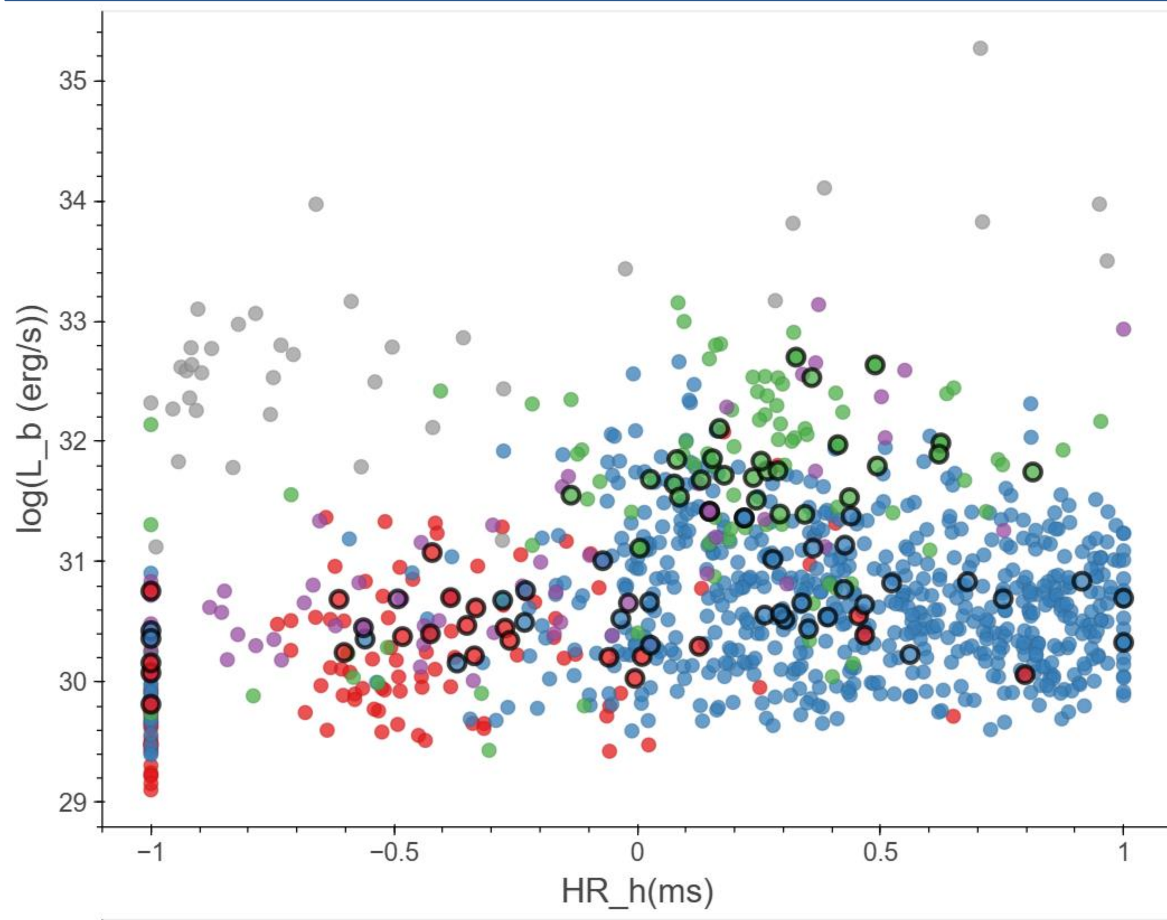
Leave-One-Out Cross-Validation



- Confusion matrices are shown for 10 runs, each run randomly sampling feature uncertainties.
- Most classes perform well, MSPs and CVs perform less well.
  - Matrix for confident classifications (>60% trees in all runs voting for class) is much more diagonal.
- Wrong classifications due to diversity within source class, lack of counterparts, similarity to other classes.

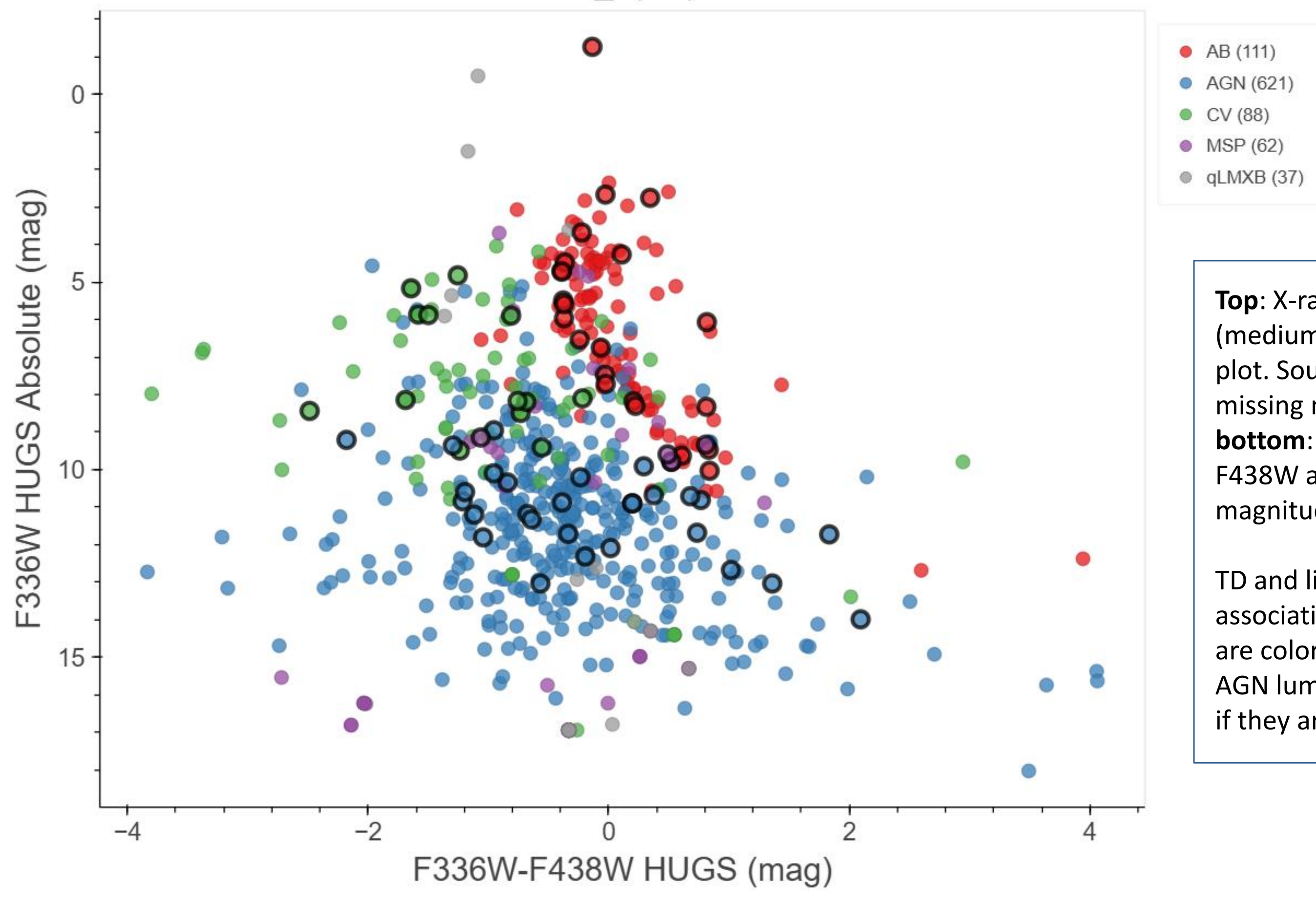
Classified Likely Associations

- Accurate classification heavily depends on finding true counterpart.
- No systematic astrometric offset between CSC and HST sources is found.
- CVs can give us a clue, as they are tightly grouped and distinct in X-ray and optical feature space:
  - More luminous and harder in X-rays compared to ABs and AGNs
  - Counterpart in white dwarf sequence, which is less common than main sequence
- We found 15 sources fulfilling these criteria:
  - Similar to TD CVs in X-rays, with significant probability to be classified as CV ($P_{CV} > 0.2$)
  - Has possible counterpart in white dwarf sequence, classified as CV
  - This counterpart is closest counterpart, often by wide margin ($<0.2''$ separation)
  - 6 are known CVs in Omega Cen, which are each removed from TD before being classified
- These are highly likely to be true CV associations, and we apply these criteria to find likely associations of other classes
- MSPs mostly lack counterpart in TD, classified MSPs largely based on X-ray information



Class	Closest CP	Likely
AGN	120	32
MSP	23	5
CV	29	26
AB	48	22
qLMXB	1	1

Classification summary of sources in ω Cen. Likely classifications found using procedure described above, and includes 6 CVs, 4 ABs, 4 AGNs, 1 MSP, and 1 qLMXB previously known.

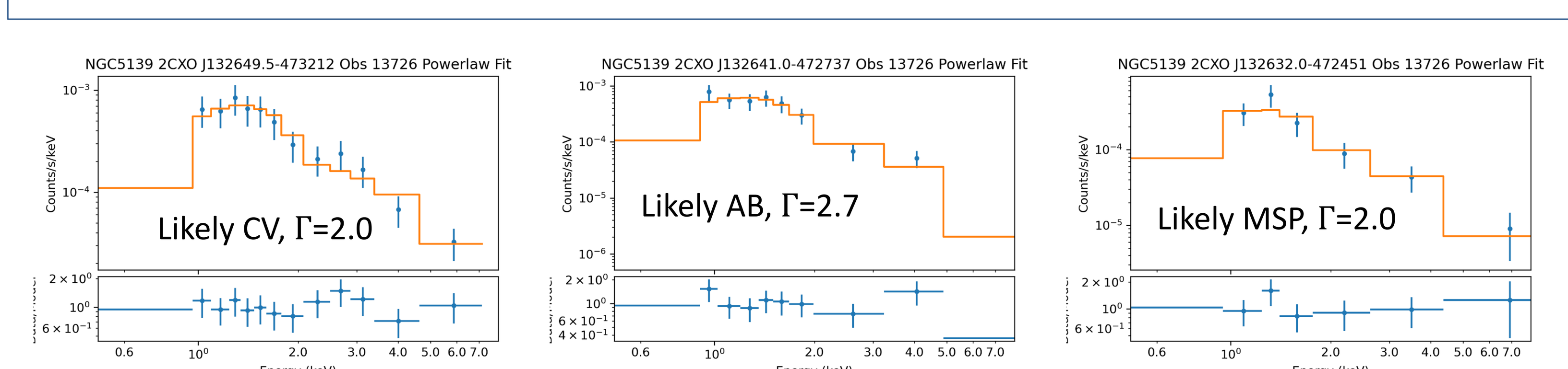


Top: X-ray Luminosity vs hard-(medium+soft) hardness ratio plot. Sources at HR_h(ms) = -1 missing medium or soft band. **bottom**: HST F336W vs F336W-F438W absolute color-magnitude diagram.

TD and likely classified ω Cen associations (outlined in black) are colored by class. AGN luminosities calculated as if they are at cluster distance.

Discussion

- Clear separation between the classes in the TD can be seen, while likely classifications have nearest counterparts that are also close in expected regions.
- 21 sources with known class in ω Cen can be used to check accuracy, when removed from TD
  - 14 sources are classified correctly using the correct association from publication
  - Most incorrect classifications are MSPs or spider MSPs
- Few MSPs pass criteria, while more are classified based on only X-ray information
  - Some with sufficient counts for spectral analysis, see plots below
  - Spectra consistent with MSPs, but other classes also possible
  - Large photon index ($\Gamma \gtrsim 3$) may imply substantial thermal emission contribution



Summary and Future Work

- MUWCLASS is a powerful tool for rapidly classifying many sources in different environments
  - Rapid classification of all associations enables finding metrics to identify true associations
  - Can substantially increase statistic for population studies of confidently classified source classes, e.g., flaring stars, AGNs, CVs
  - Identify unusual/interesting sources for more detailed study, e.g. MSP candidates
- Future work:
  - Classify X-ray sources in all applicable GCs
  - Integration of additional sensitive surveys, including radio
  - Expansion of TD: living database of classified X-ray sources

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