Predicting Follow-Up Observations of Galaxy Clusters Using Machine Learning

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Background

- Galaxy Clusters are the most massive gravitationally bound objects in the Universe
- They are a useful probe of both dark matter physics and cosmology
- Have areas of active research that require further observation to resolve
  - Mass estimation bias
  - Core-cooling

Outstanding Questions

- Mass Estimation Bias
  - Mass abundances of galaxy clusters useful for constraining cosmology (Pratt+19)
  - X-ray observations provide low-scatter mass estimates (e.g., Kravtsov+06)
  - Reliant on mass proxies, introduce bias (e.g., Shi+15)
  - Dynamical state important source of mass estimate bias
- Cluster populations show different behaviors in the core (cool vs non-cool) (e.g., Inoue+22)
  - Further observations would improve understanding

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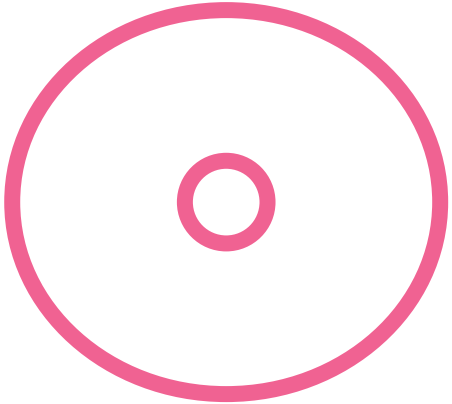
Motivation

- eROSITA will observe many more Galaxy Clusters (Merloni+12)
- Follow-up observations with higher spatial resolution longer duration instruments is essential
- Follow-up is expensive
- Need a tool to evaluate the merit of follow-up

Follow-Up Merit Assessment Tool

- Want to predict follow-up observations while preserving parameters of interest
- Morphology correlated to galaxy cluster dynamical state (e.g., Rasia+13), core type (e.g., Santos+08), and mass (e.g., Green+19)
- Focus on preserving cluster morphology (Green+19):
    - Concentration
    - Asymmetry
    - Smoothness

Morphology Parameters



- **C**oncentration
  - Ratio of interior flux to total flux

$$C = \frac{F(r \leq .1 \times R_{500c})}{F(r \leq R_{500c})}$$

- **A**symmetry
  - Difference between image and rotation, normalized by total flux

$$A = \frac{F(|\mathbf{X} - \mathbf{X_{180}}|; r \leq R_{500c})}{F(\mathbf{X}; r \leq R_{500c})}$$

- **S**moothness
  - Difference between image and smoothed image, normalized by total flux

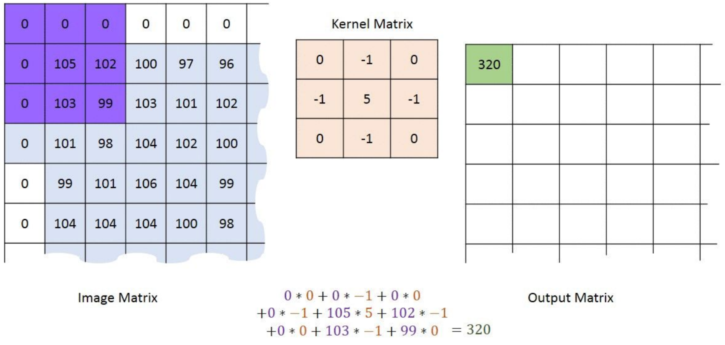
$$S = \frac{F(|\mathbf{X} - \tilde{\mathbf{X}}|; r \leq R_{500c})}{F(\mathbf{X}; r \leq R_{500c})}$$

Data

- Galaxy clusters simulated by *Magneticum* simulation (Dolag+16)
  - WMAP yr 7 cosmology (Komatsu+11)
  - 3285 clusters
  - 3E13 < M_500c < 1.17E15
  - 0.07 < z < 0.47
- Mock observations made using *PHOX* algorithm (Biffi+12, +13)
  - 10 Mpc depth, 9.6” square pixels
  - 3-band image (0.5-1.2 keV, 1.2-2.0 keV, 2.0-7.0 keV)
  - 2ks and 10ks observations
- Observation made eROSITA-like using *SIXTE* (Dauser+19)
  - Instrument Response
  - Background

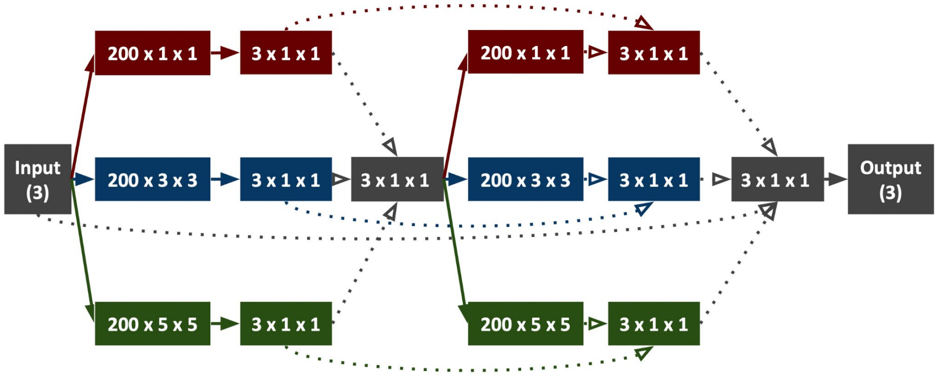
Model

Source:
https://stackoverflow.com/questions/52067833/how-to-plot-an-animated-matrix-in-matplotlib



Convolution with horizontal and vertical strides = 1

- Convolutional Neural Network
  - Machine learning model variant that preserves spatial relationship of pixels, allowing for faster learning
- Novel architecture
  - Different kernel sizes to examine relevant lengths scales in parallel



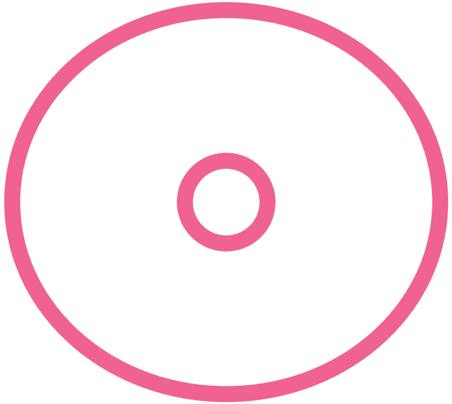
Training

- Inputs: eROSITA-like Observations
  - Background
  - Instrument response
  - 2ks observing time
- Truths: Idealized Observations
  - No background
  - No instrument response
  - 10ks observing time
- Morphology Loss function
  - Pixel MAE + Fixed Morphology MAE

Fixed Morphology Parameters

- **C**oncentration
  - Ratio of interior flux to total flux

$$C = \frac{F(r \leq 10)}{F(r \leq 100)}$$



- **A**symmetry
  - Difference between image and rotation, normalized by total flux

$$A = \frac{F(|\mathbf{X} - \mathbf{X_{180}}|)}{F(\mathbf{X})}$$

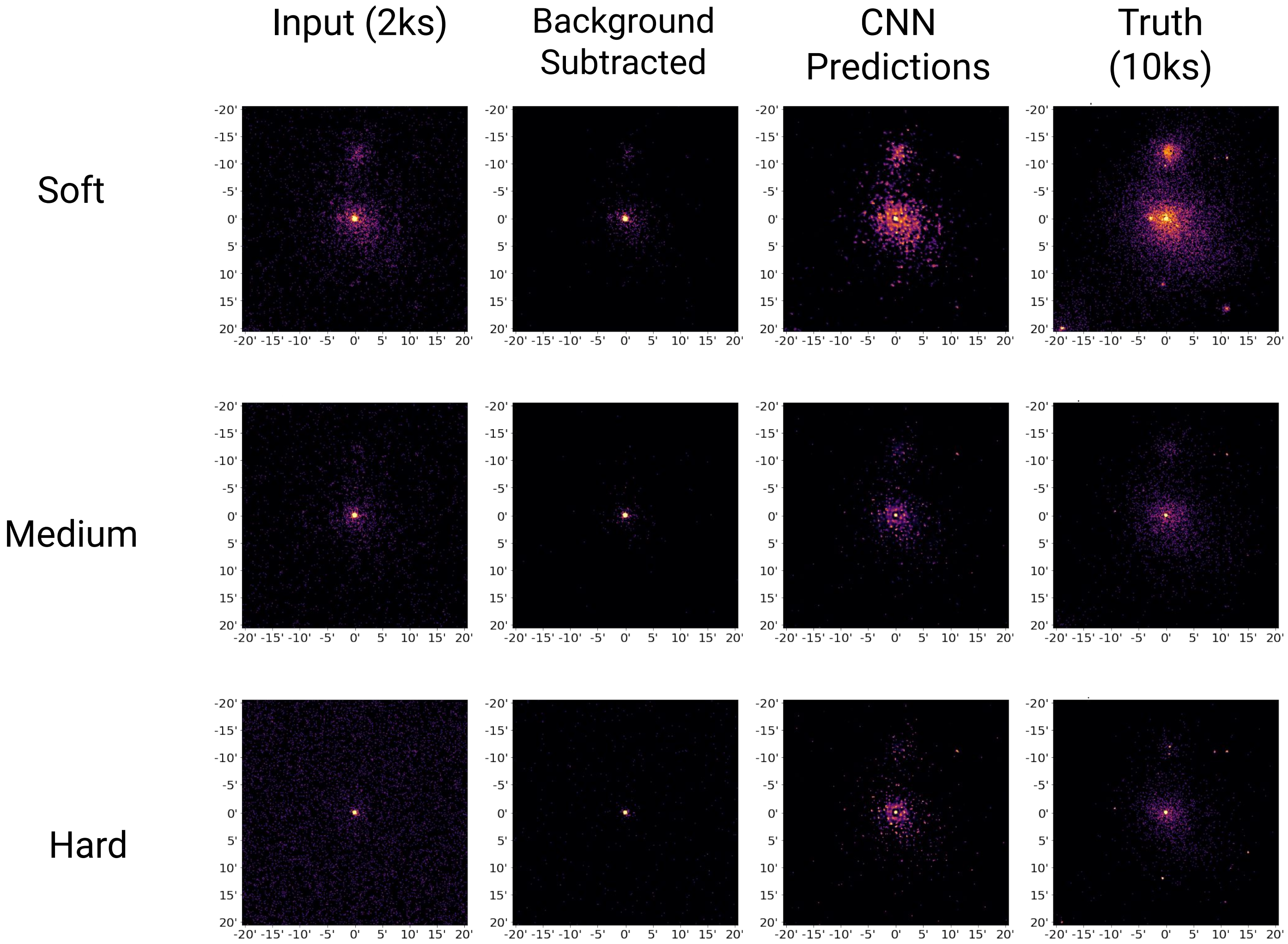
- **S**moothness
  - Difference between image and smoothed image, normalized by total flux

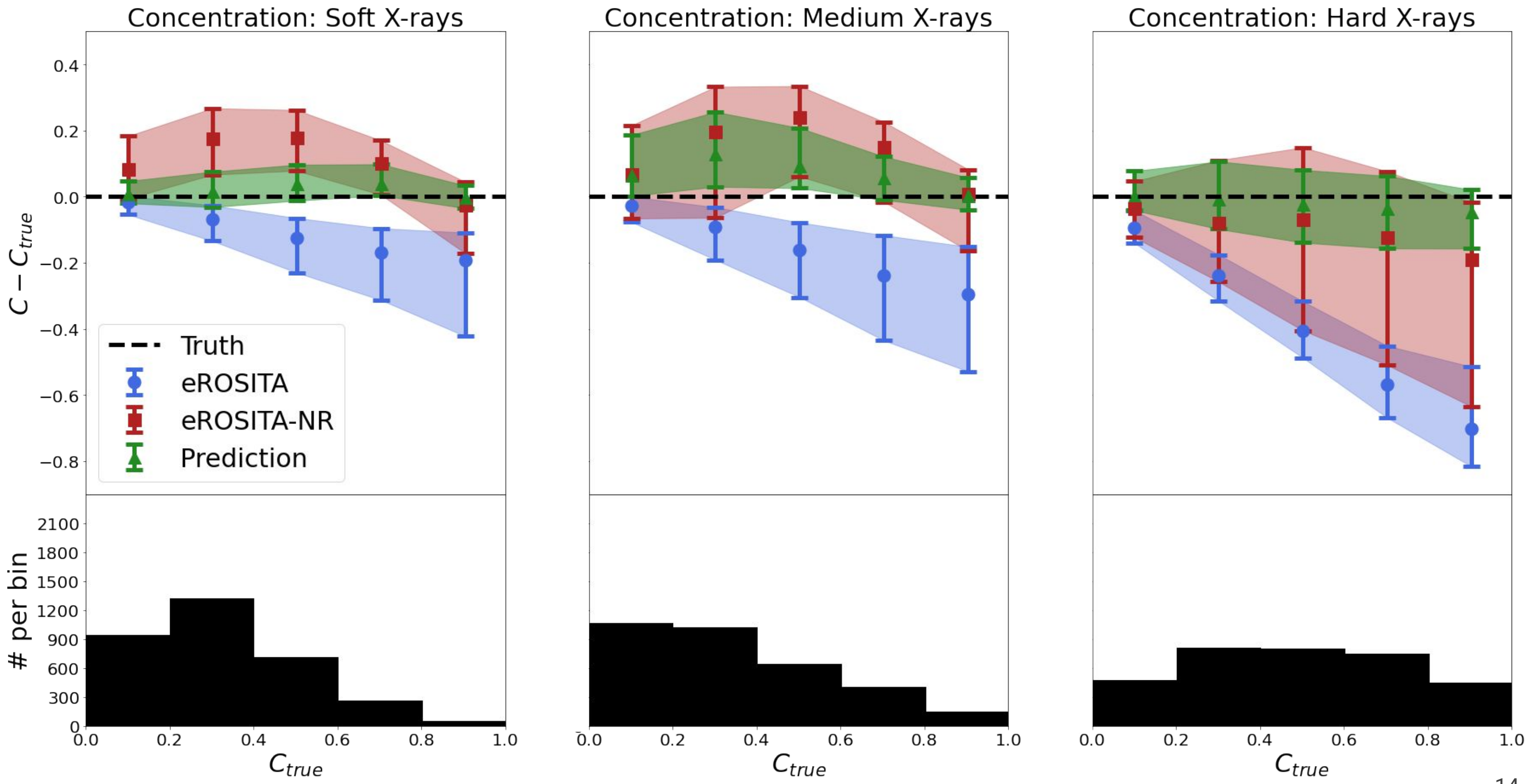
$$S = \frac{F(|\mathbf{X} - \tilde{\mathbf{X}}|)}{F(\mathbf{X})}$$

Results

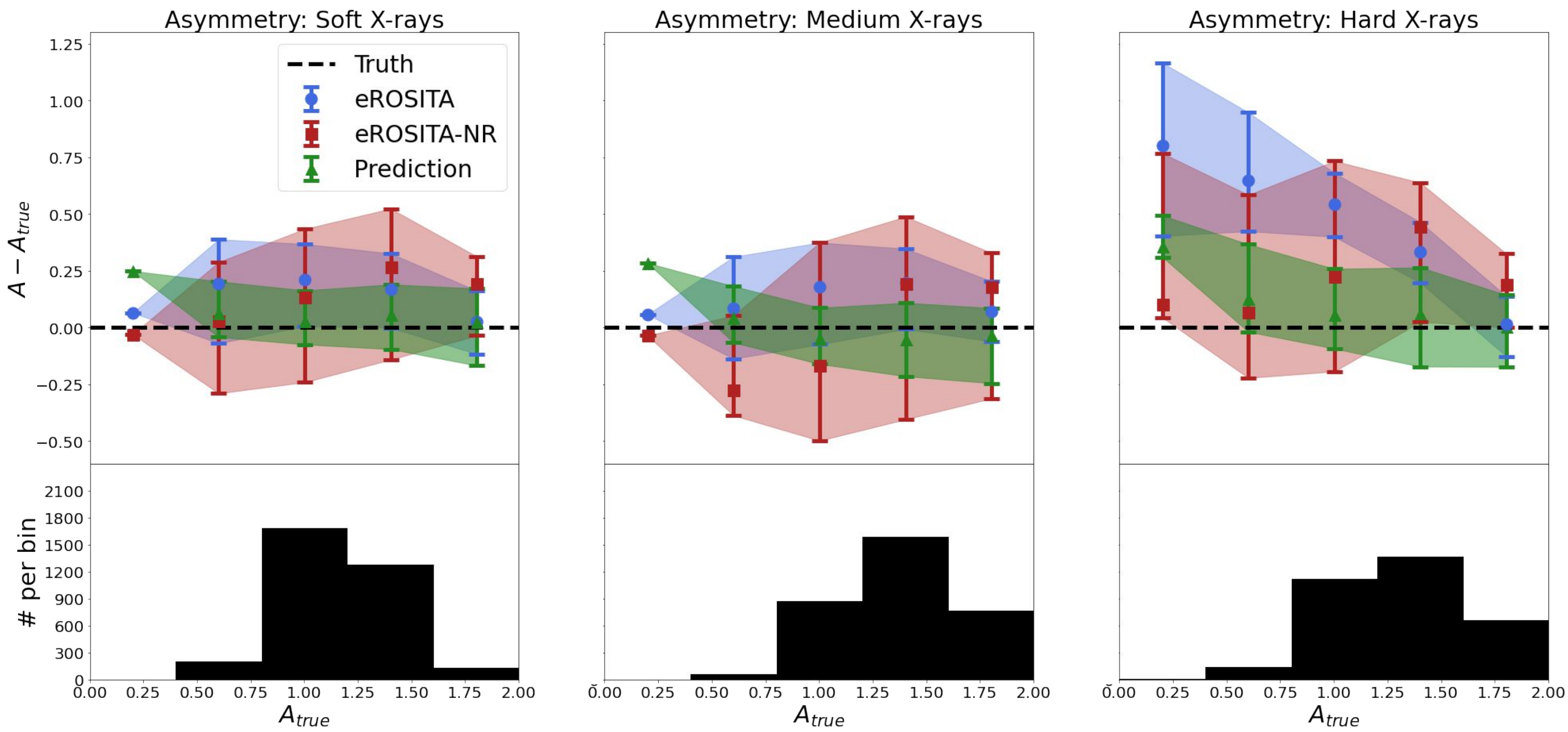
Compare Cluster Morphologies Calculated from:

- **Truth**: 10 ks observation
  - Observation type used as truths in CNN training
- **eROSITA**: eROSITA-like 2ks observations
  - Observation type used as inputs in CNN training
- **eROSITA-NR**: Background subtracted eROSITA-like 2ks observations
  - A simple alternative non-machine learning method for comparison
- **Prediction**: CNN model outputs

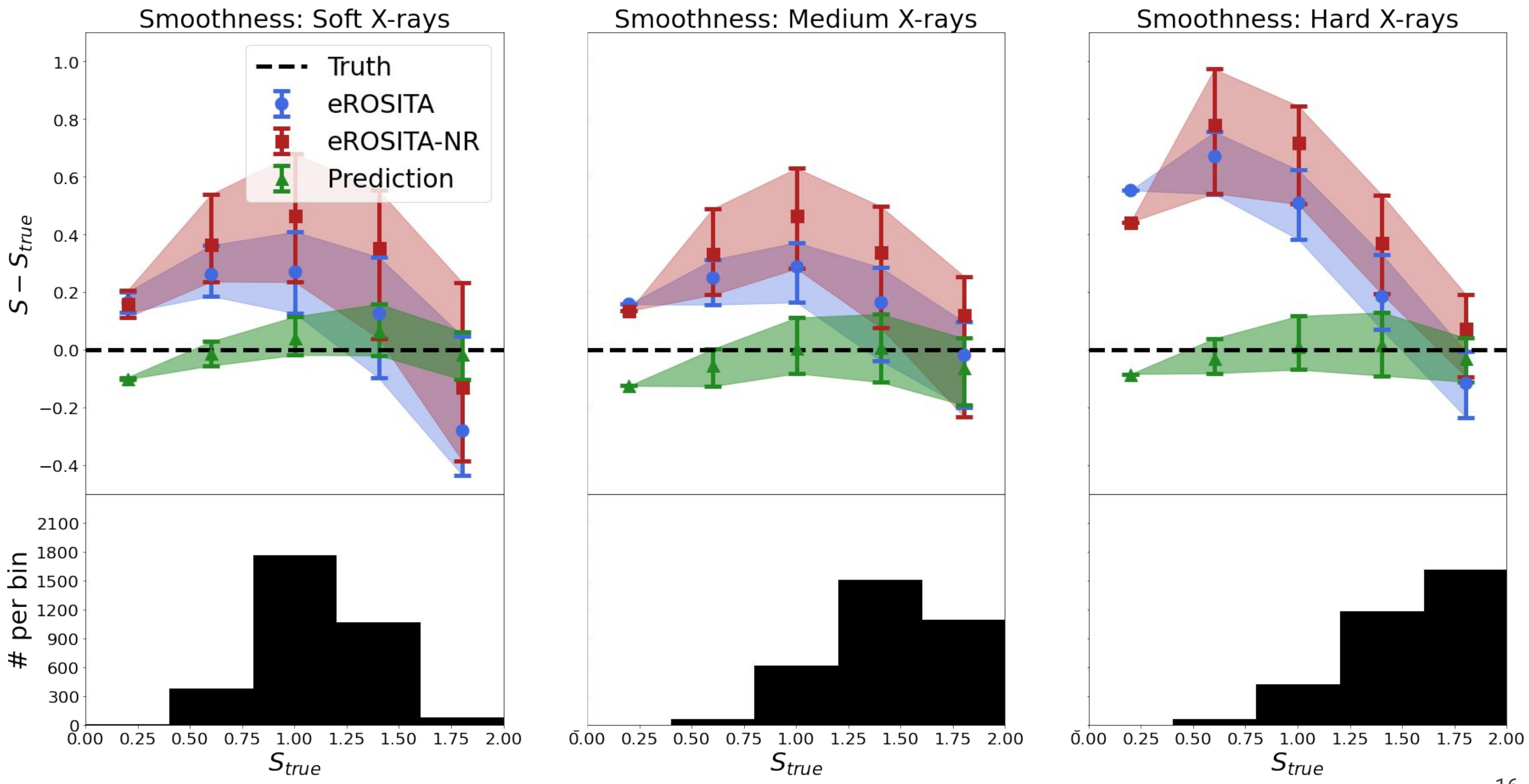

Input (2ks)
Background Subtracted
CNN Predictions
Truth (10ks)
Soft
Medium
Hard
-20' -15' -10' -5' 0' 5' 10' 15' 20'



Concentration: Soft X-rays
Concentration: Medium X-rays
Concentration: Hard X-rays
$C - C_{true}$
per bin
C_{true}
Truth
eROSITA
eROSITA-NR
Prediction



Asymmetry: Soft X-rays
Asymmetry: Medium X-rays
Asymmetry: Hard X-rays
Truth
eROSITA
eROSITA-NR
Prediction
$A - A_{true}$
per bin
A_{true}
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
2100
1800
1500
1200
900
600
300
0
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00



Smoothness: Soft X-rays
Smoothness: Medium X-rays
Smoothness: Hard X-rays
Truth
eROSITA
eROSITA-NR
Prediction
$S - S_{true}$
per bin
S_{true}
S_{true}
S_{true}

Domain Shift

- Models trained on simulated data are biased when applied to real data
  - Differences between simulations and reality bias model predictions (Amodei+16)
- Potential solution using transfer learning
  - Additional train on pairs of real cluster observations (eROSITA & Follow-up) can make model more robust to domain shift

Summary

- Galaxy clusters are important probes of cosmology and laboratories of astrophysics
- Outstanding questions remain regarding galaxy cluster dynamical state and core cooling
  - Follow-ups of soon-to-be-released data are essential to answer these questions, but follow-up is expensive
- **Prediction of morphologically accurate, long-duration, background-free galaxy cluster observations is possible with deep learning**