

# Decoding Dark Matter Substructure without Supervision

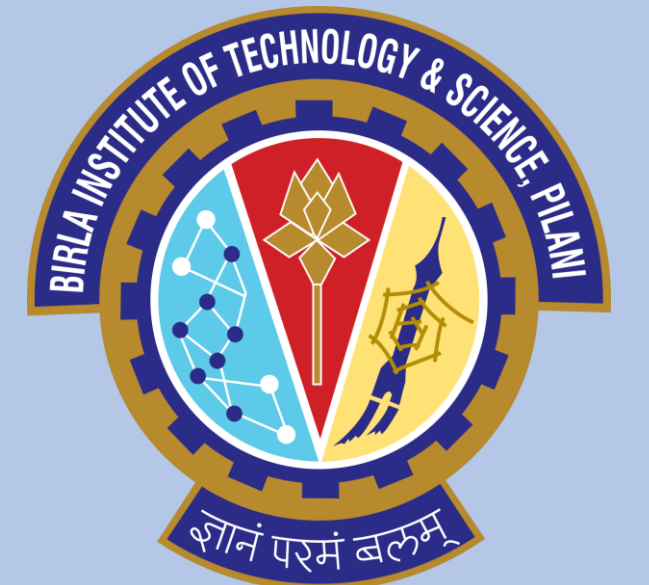
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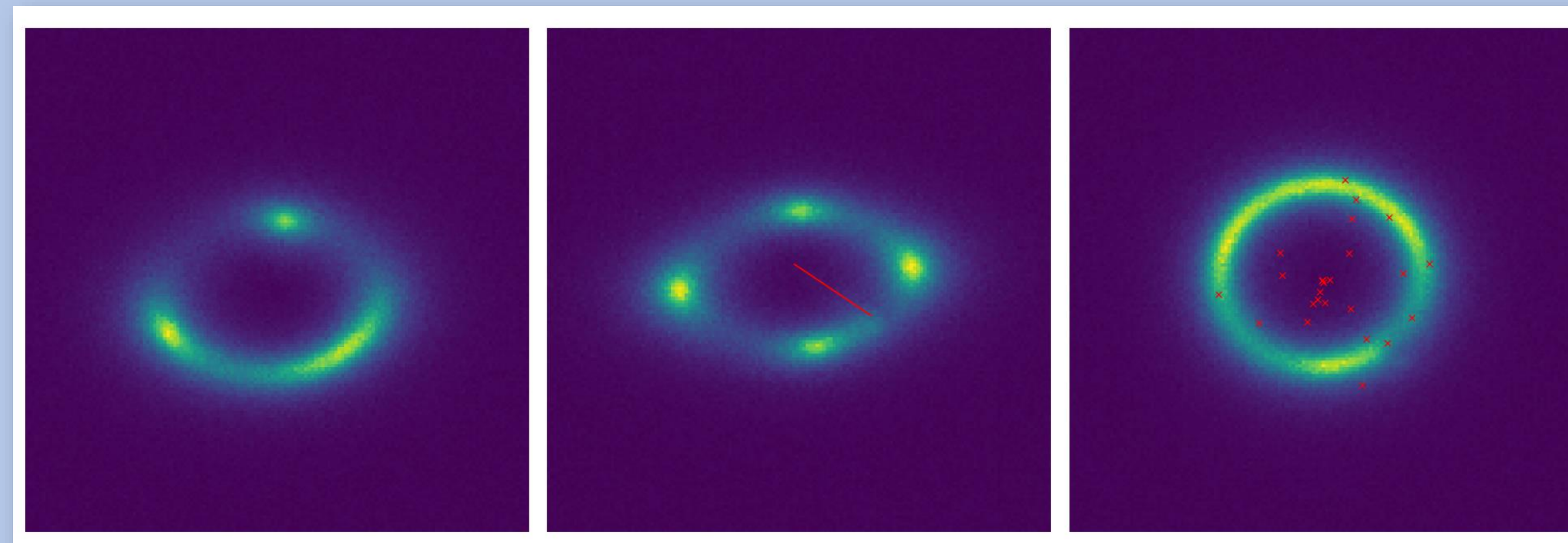
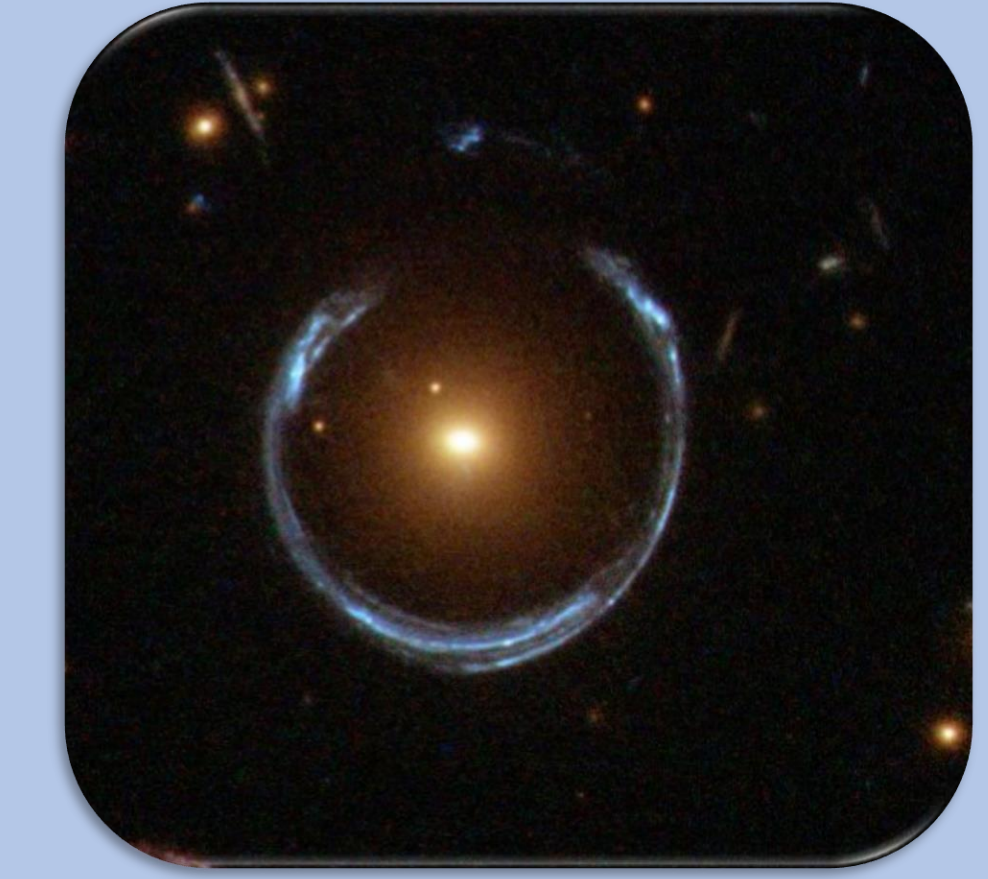


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## Goal: Identify and/or constrain models of dark matter based on gravitational signature

- Different DM models can have disparate substructure - subhalos, vortices, disks
- Promising probes include astrometric measurements, tidal streams, and gravitational lensing
- Extended lensing arcs of galaxy-galaxy strong lensing images are sensitive to perturbations induced by substructure



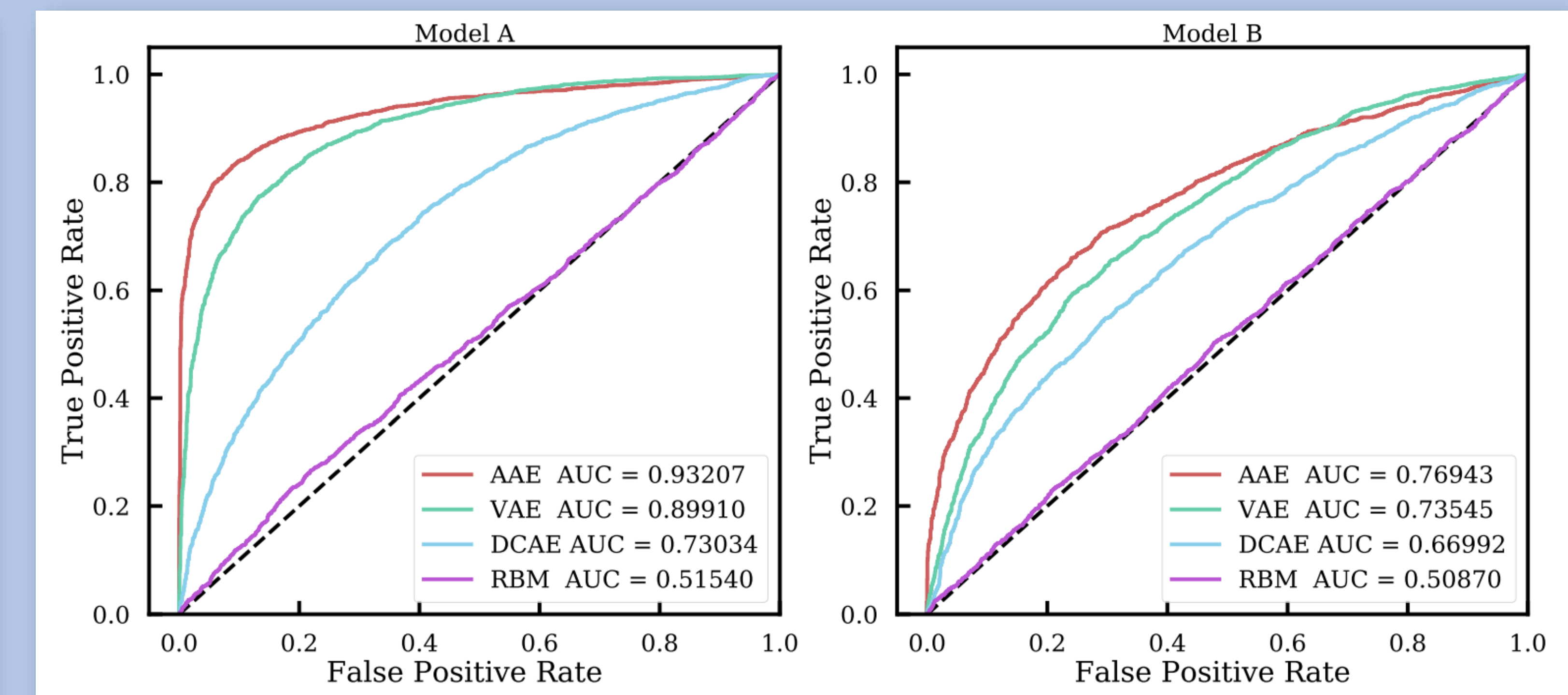
## Method: Implement an anomaly detection approach to identify images with substructure

- Training data - simulations of galaxy-galaxy strong lensing with vortex, subhalo, and no substructure using PyAutoLens software
- Train restricted Boltzmann machine, adversarial, variational, and deep convolutional autoencoders on data with no substructure to flag data with substructure as anomalous.
- Classify architecture performance with AUC and Wasserstein distance

## Results: Our autoencoder architectures perform well at identifying images with arbitrary substructure!

- We calculate the AUC values from the distribution of reconstruction loss
- As an additional metric, we calculate the Wasserstein distance, a geodesic distance between probability distributions, to quantify how well architecture reconstructs images
- Our autoencoder architectures perform well at identifying data with substructure and the RBM performs poorly
- Anomaly detection models can identify substructure, however, automatically disentangling different forms of substructure still presents a challenge better addressed by supervised models

Architecture	AUC	$W_1$
<b>Model A</b>		
ResNet-18	0.99637	
AAE	0.93207	0.22112
VAE	0.89910	0.22533
DCAE	0.73034	0.26566
RBM	0.51054	1.27070
<b>Model B</b>		
ResNet-18	0.99258	
AAE	0.76943	0.15563
VAE	0.73545	0.16617
DCAE	0.66992	0.23653
RBM	0.50870	1.25804



## Future work:

- Construct higher fidelity simulations
- Consider lensing effects from other dark matter models
- Train graph-based models more suitable for sparser data