Deep learning approaches to galaxy merger identification and classification

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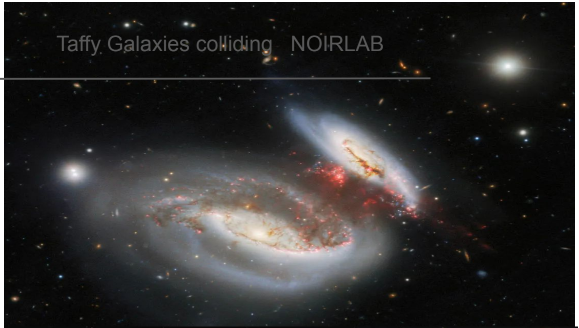
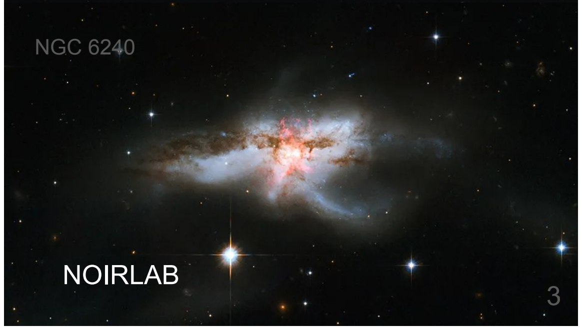
NATIONAL CENTRE FOR NUCLEAR RESEARCH ŚWIERK

Why galaxy mergers are important?

- **Shapes the galaxies** – mergers alter galaxies' structure, size, and dynamics.
- **Triggers star formation** – interactions compress gas clouds, triggering bursts of star formation.
- **Fuel AGN activity** – mergers channel gas to galactic centers, fueling active nuclei.
- **Redistributing material** – stars, gas, and metals are mixed and spread across galaxies.





Why galaxy mergers are important?

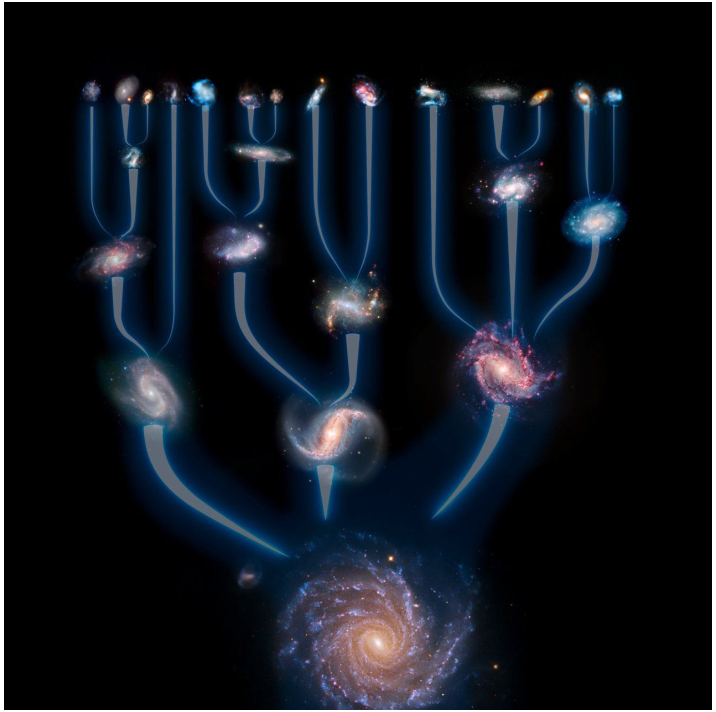


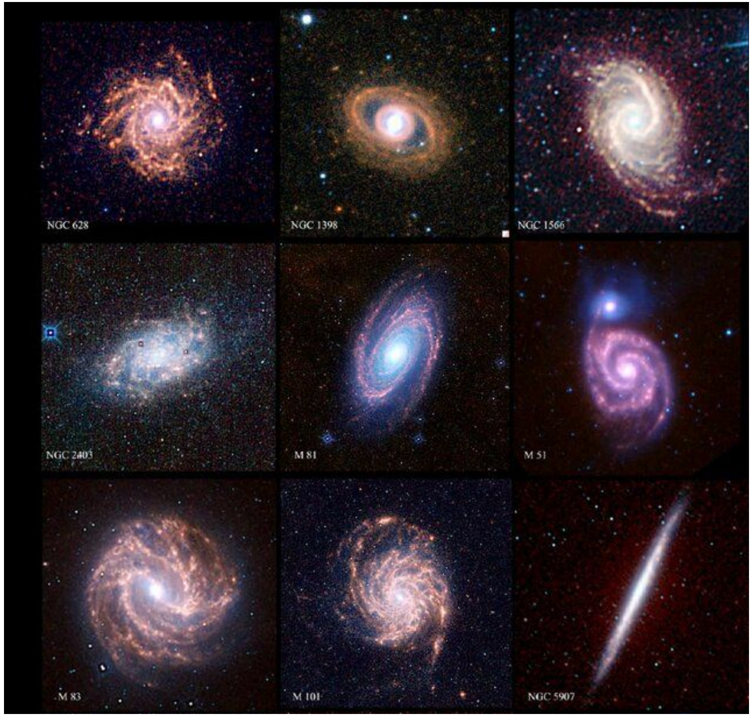
Image credit: ESO

- **Galaxy Growth** – hierarchical merging is a key pathway for building massive galaxies.
- **Tracing Cosmic Evolution** – merger rates reflect how structure forms across cosmic time.

Mergers are fundamental drivers of galaxy evolution.

Merger identification : Visual Classification

1



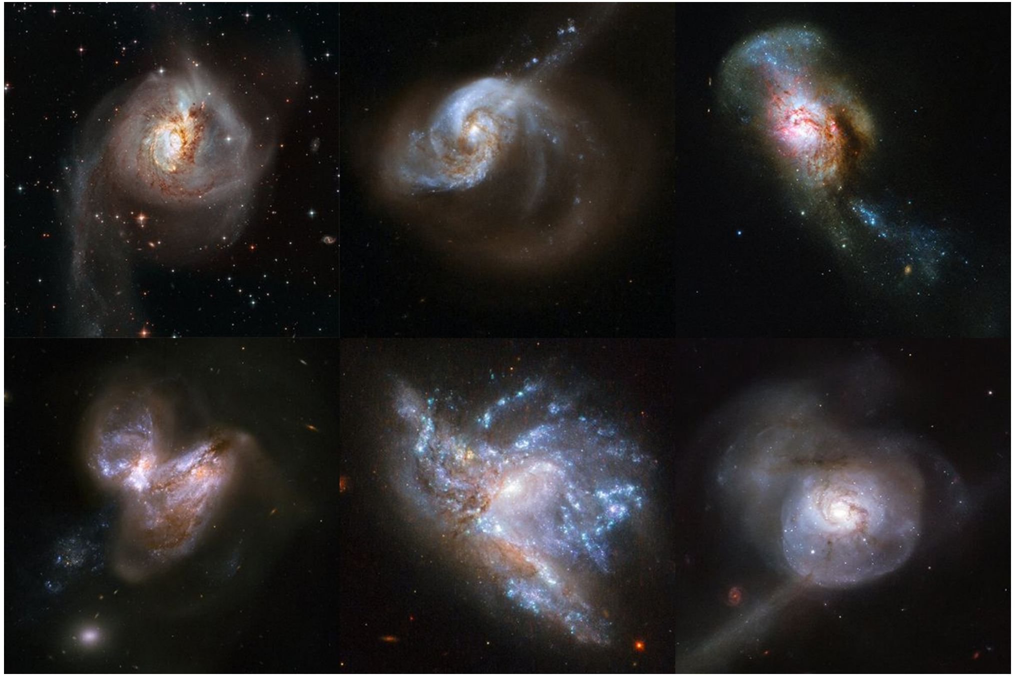
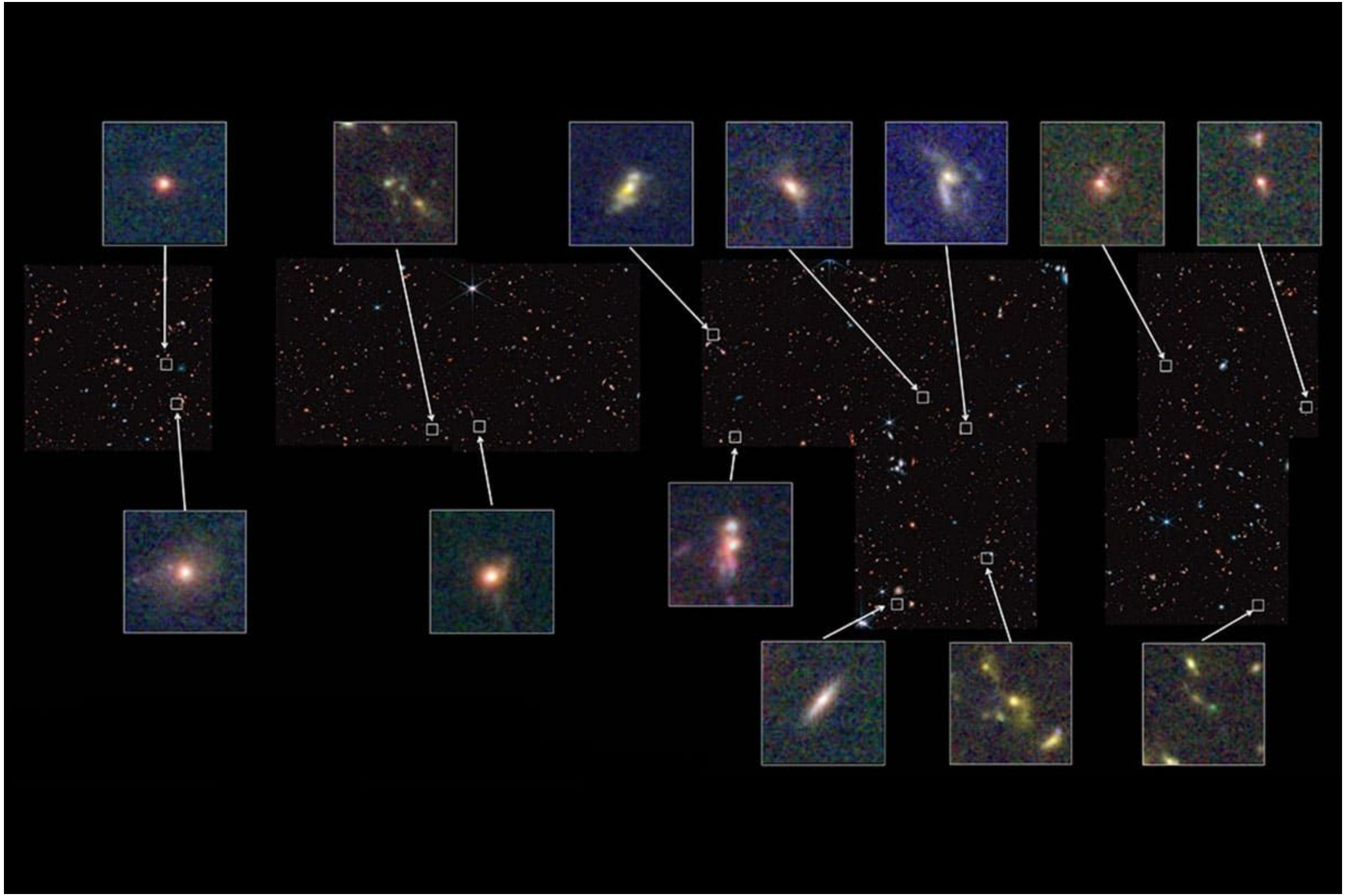


Image credit: ESA

Merger identification : Visual Classification

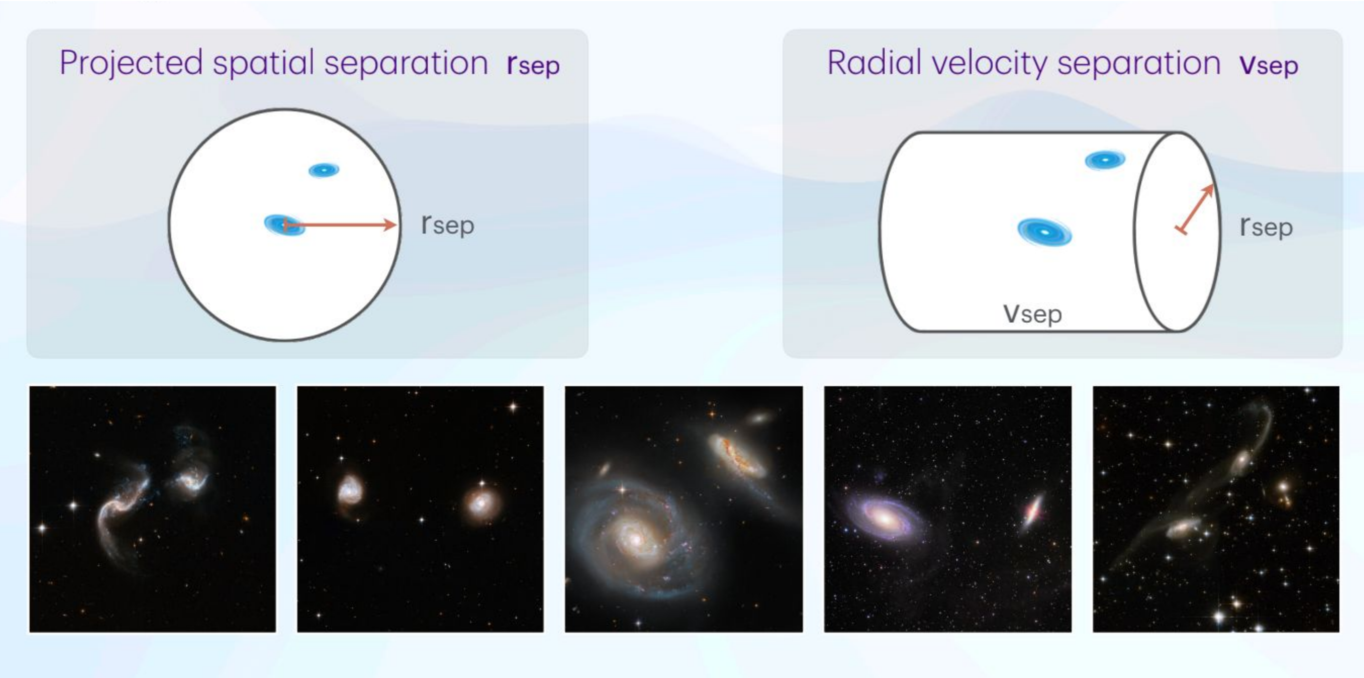


Merger identification : Close Pair

2

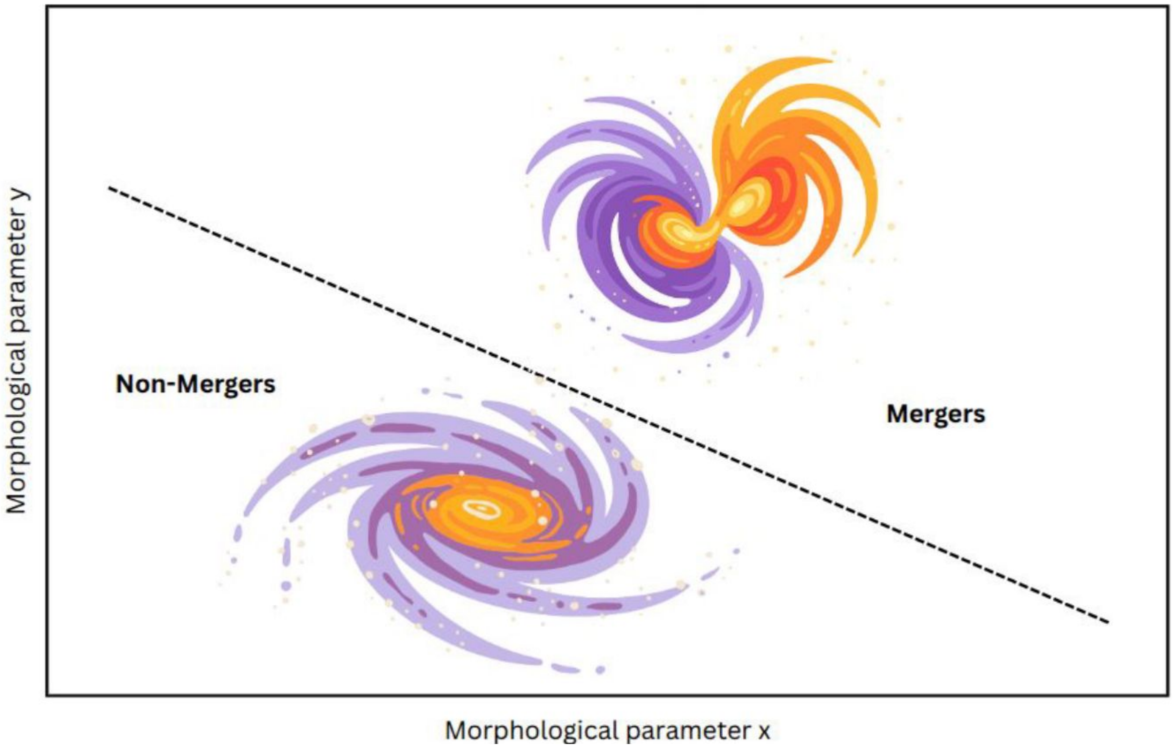
Galaxies close on the sky (< 20–50 kpc)

Small relative line-of-sight velocity difference (e.g. ≤ 500 km/s)



Merger identification: Morphological cuts

3

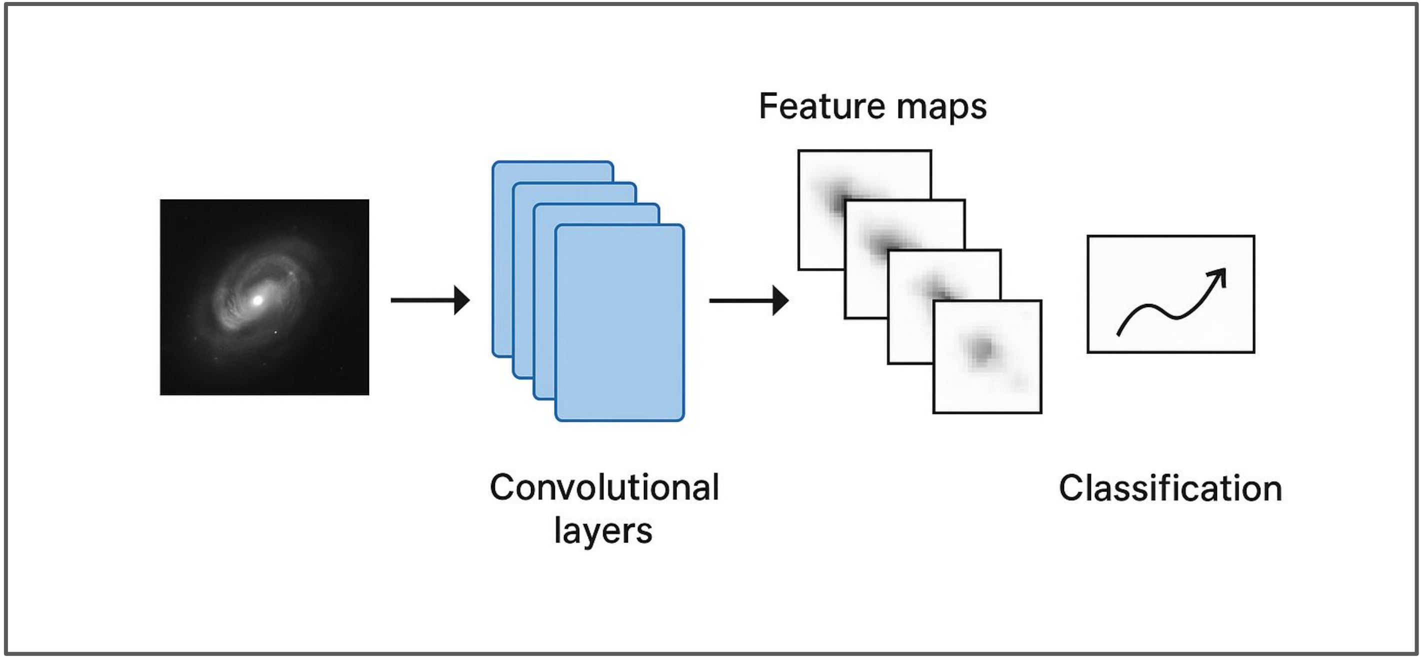


Slide Credit: Aidan Cotter

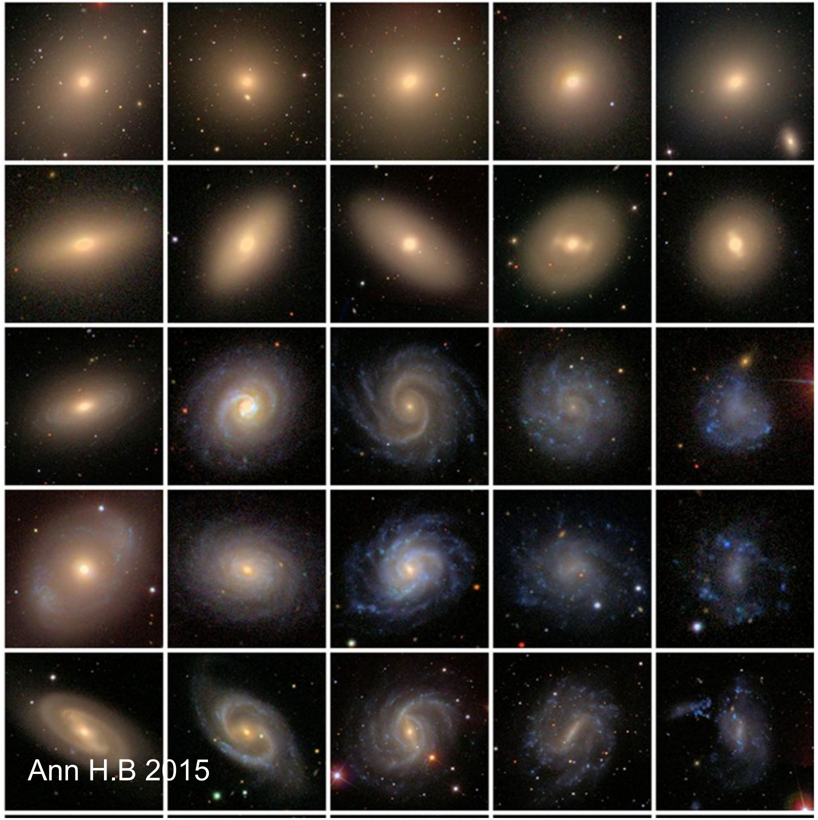
Merger identification : Deep learning

4

- ★ Powerful approach for automatically classifying galaxy mergers from imaging data
- ★ It learn patterns from data, making it ideal for complex tasks like galaxy classification.



AIM: Going beyond merger / non-merger classification



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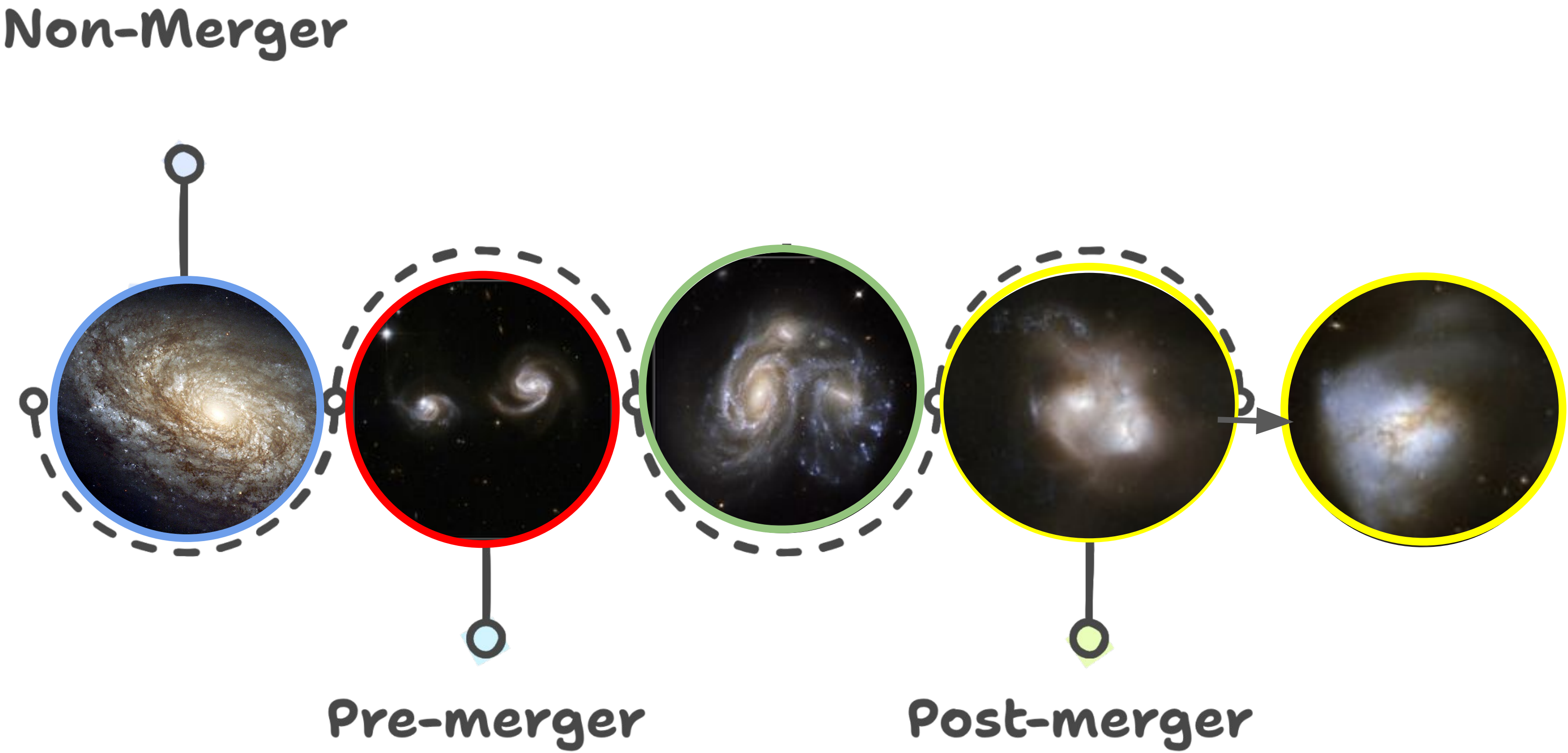


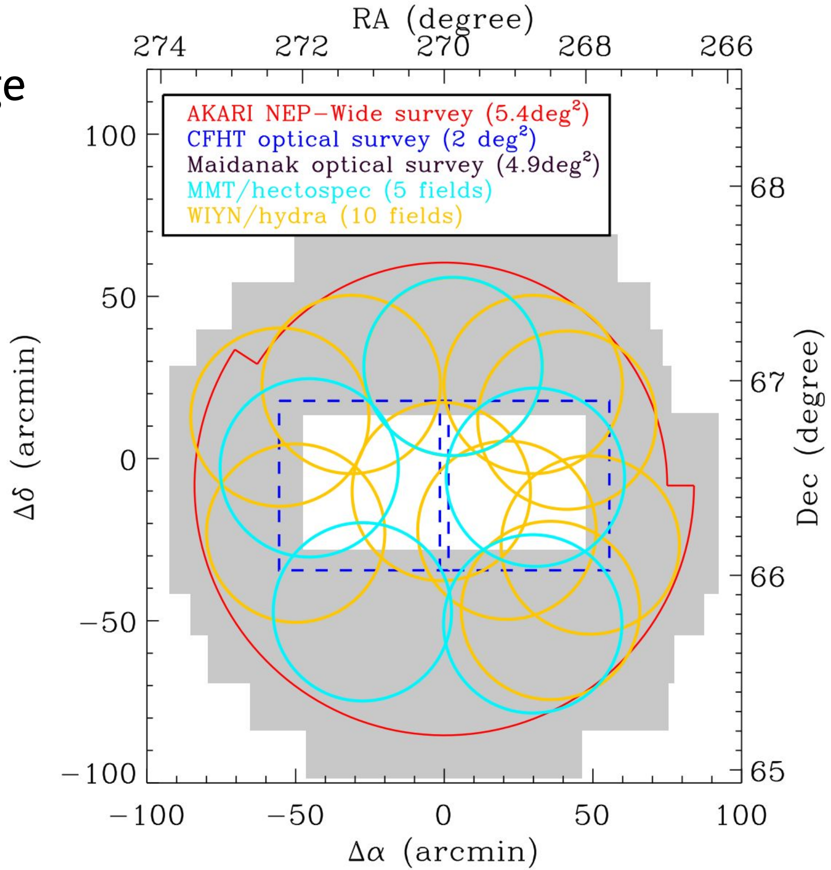
AIM: Creating science ready catalogue

NEP field : 5.4 deg², multi-wavelength coverage

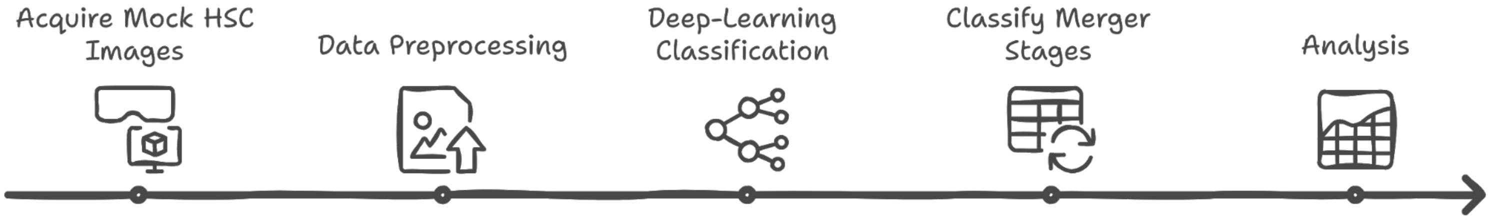
Xray → Radio

👉 Create a catalog of the NEP field including:

- **Non-mergers**
- **Pre-mergers**
- **Post-mergers**



Workflow for Galaxy Merger Classification



Mock Images

Acquire Mock HSC Images

THE GALAXY MERGER CHALLENGE

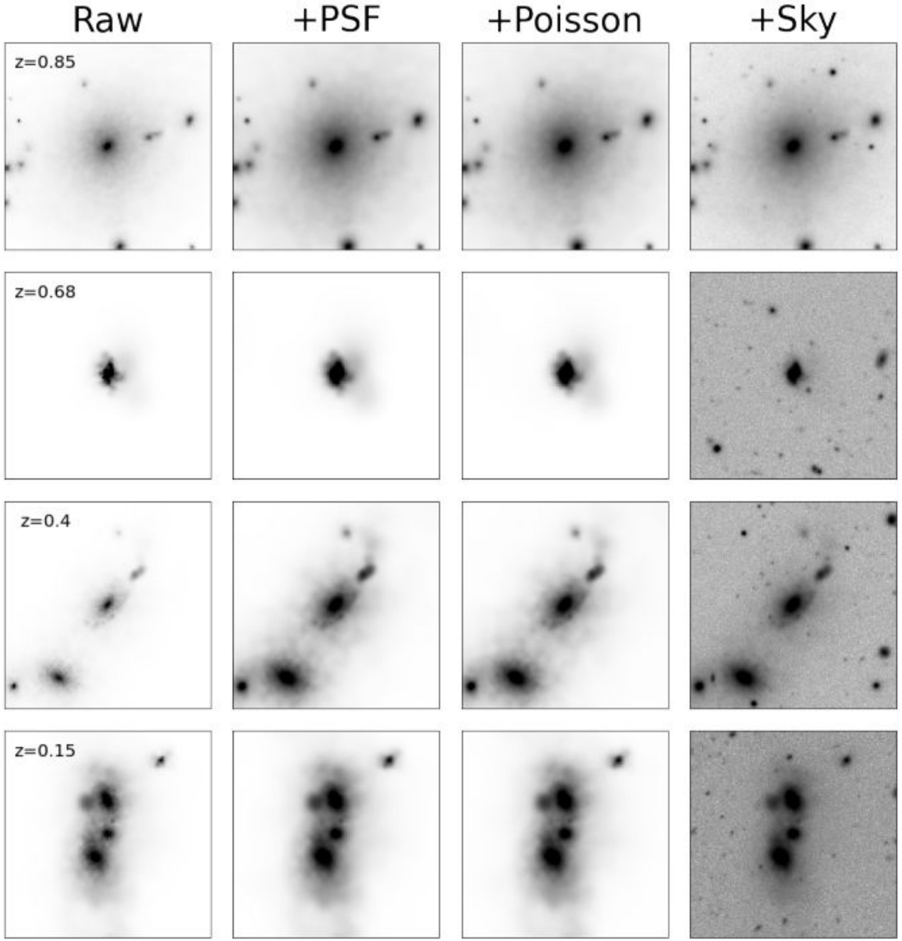
A&A, 687, A24 (2024)
https://doi.org/10.1051/0004-6361/202348239

Astronomy & Astrophysics

Galaxy merger challenge: A comparison study between machine learning-based detection methods

B. Margalef-Bentabol[1], L. Wang[1,2], A. La Marca[1,2], C. Blanco-Prieto[3], D. Chudy[4], H. Domínguez-Sánchez[5], A. D. Goulding[6], A. Guzmán-Ortega[7], M. Huertas-Company[8], G. Martin[9,10], W. J. Pearson[11], V. Rodriguez-Gomez[7], M. Walmsley[12], R. W. Bickley[13], C. Bottrell[14], C. Conselice[12], and D. O'Ryan[15]

Mock HSC images

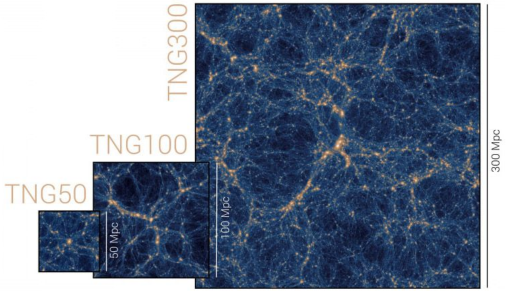


Simulations:

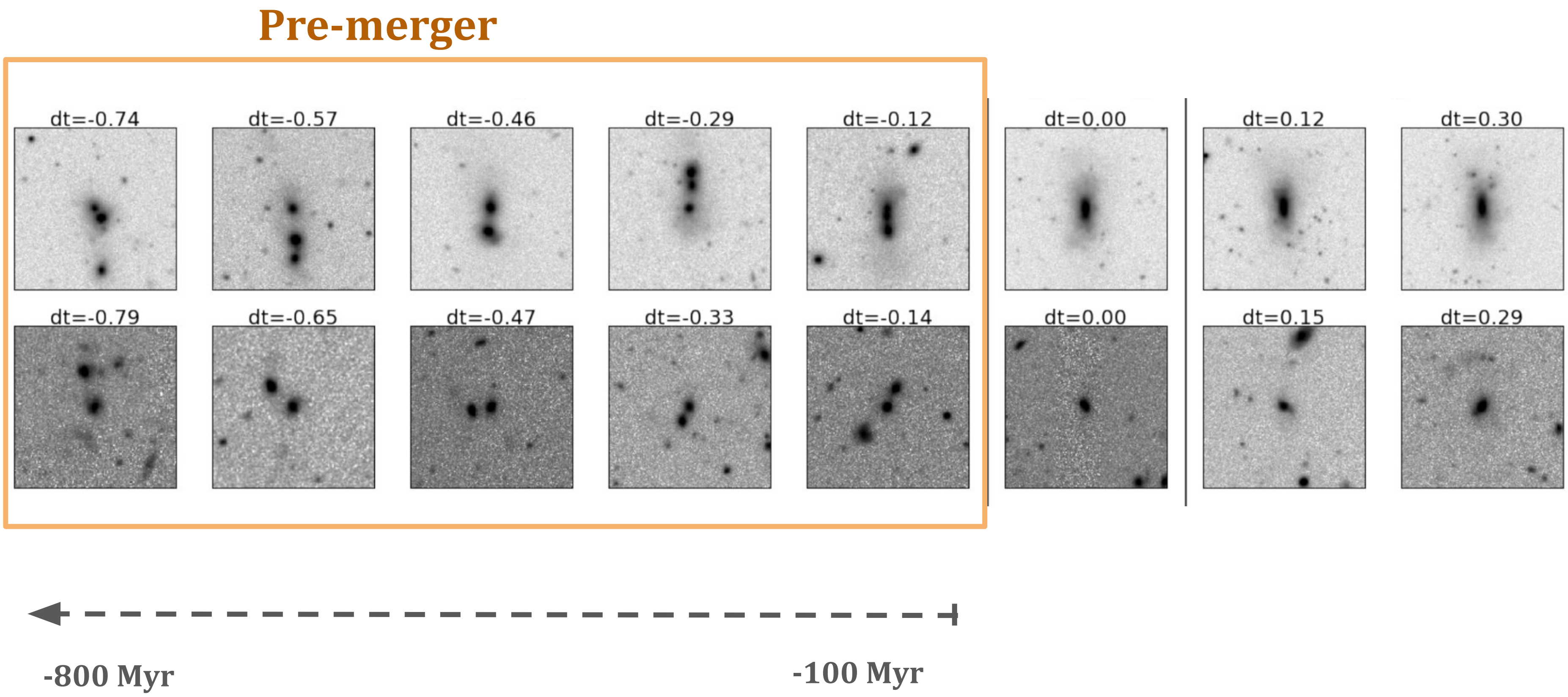
TNG300 → chosen for its large number of galaxies

TNG100 → included to probe lower-mass galaxies

Redshift range: 0.1 - 1.0



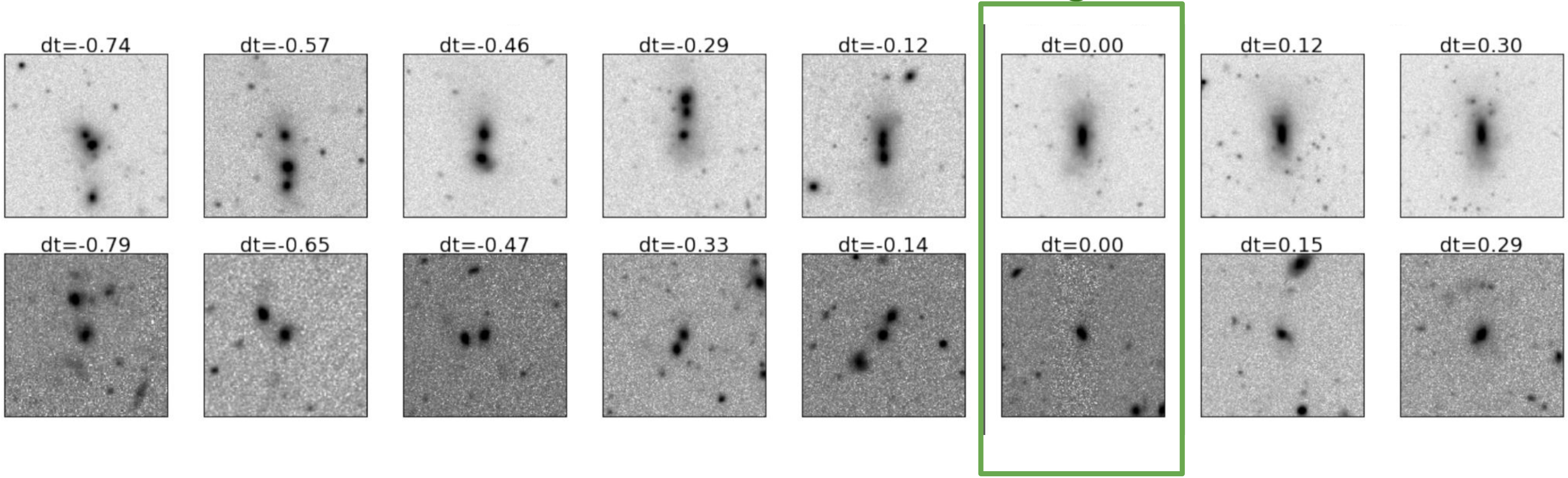
Merger definition



Merger definition

Pre-merger

Ongoing Merger

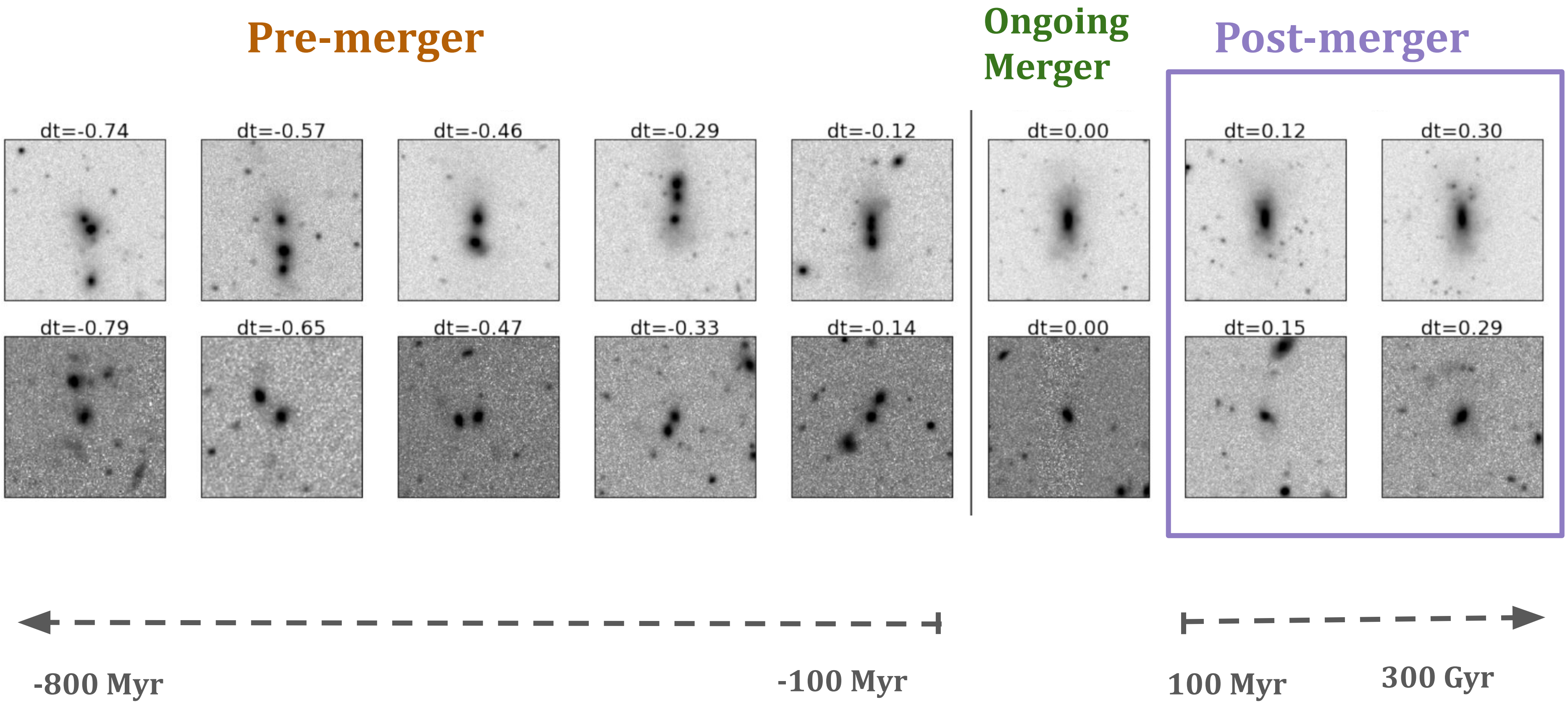


-800 Myr

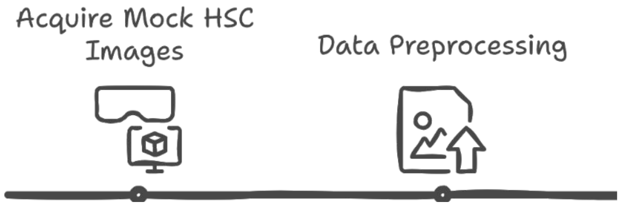
-100 Myr

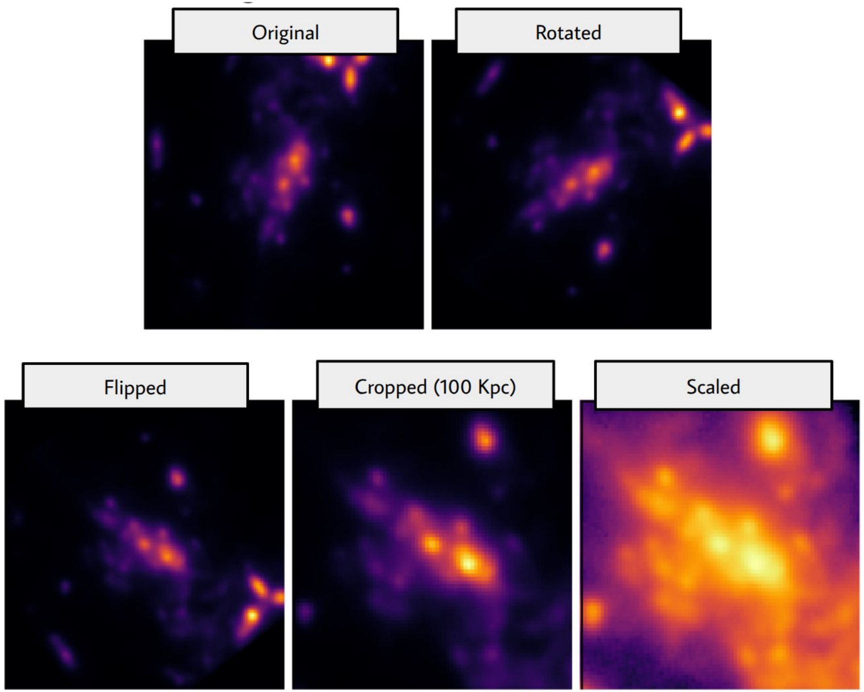
100 Myr

Merger definition

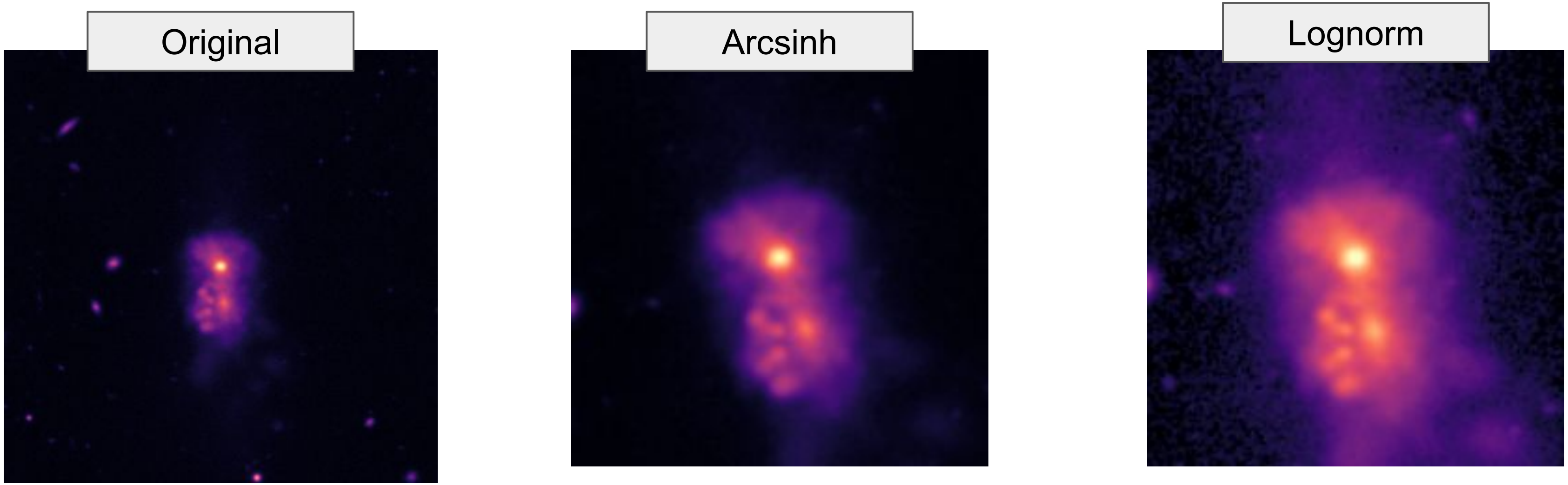


Data preprocessing

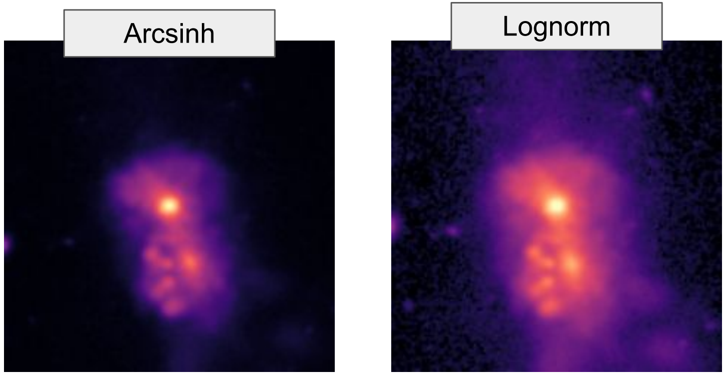




Data preprocessing



Deep learning merger classification



Base deep learning networks:

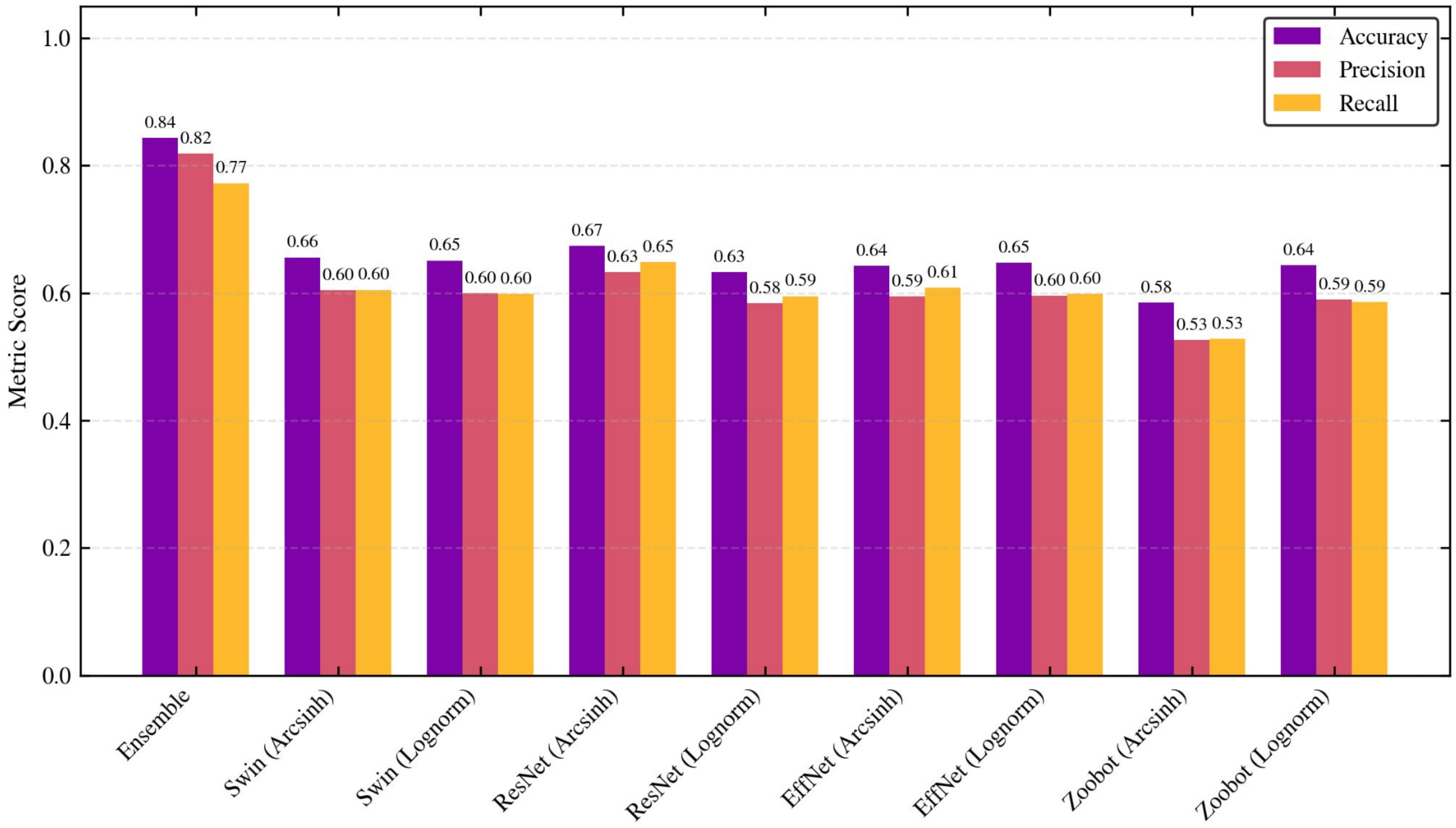
- Zoobot ConvNeXt
- EfficientNet-B3
- ResNet-18
- Swin Transformer (SwinT)

Ensemble :

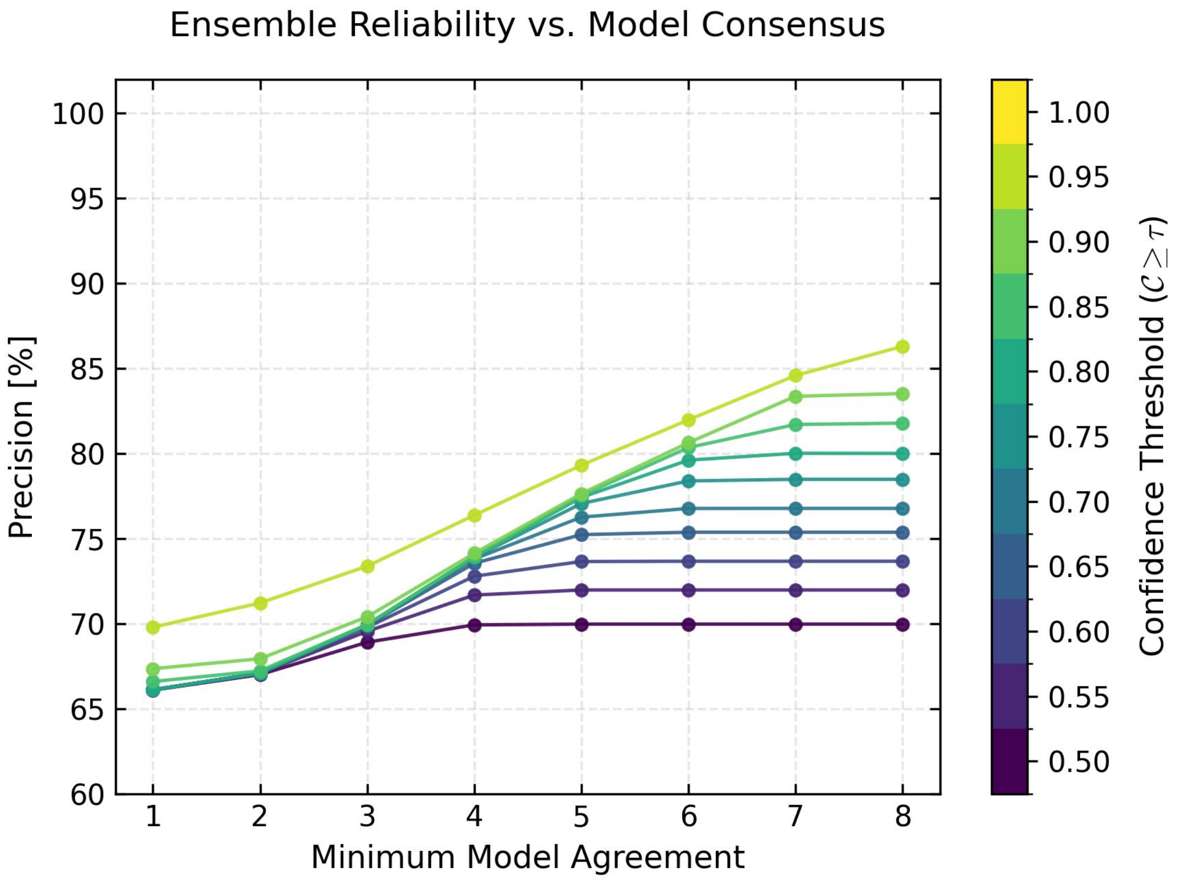
Combination of 8 independently trained models

Final prediction obtained via ensemble voting

Classifier performance



Ensemble performance



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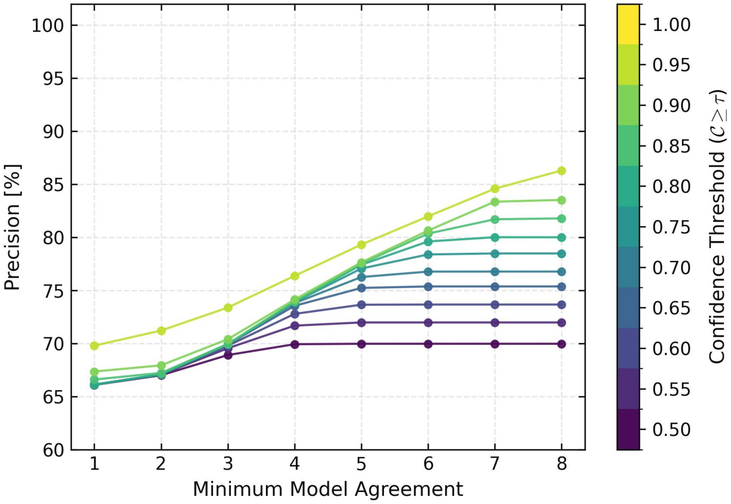
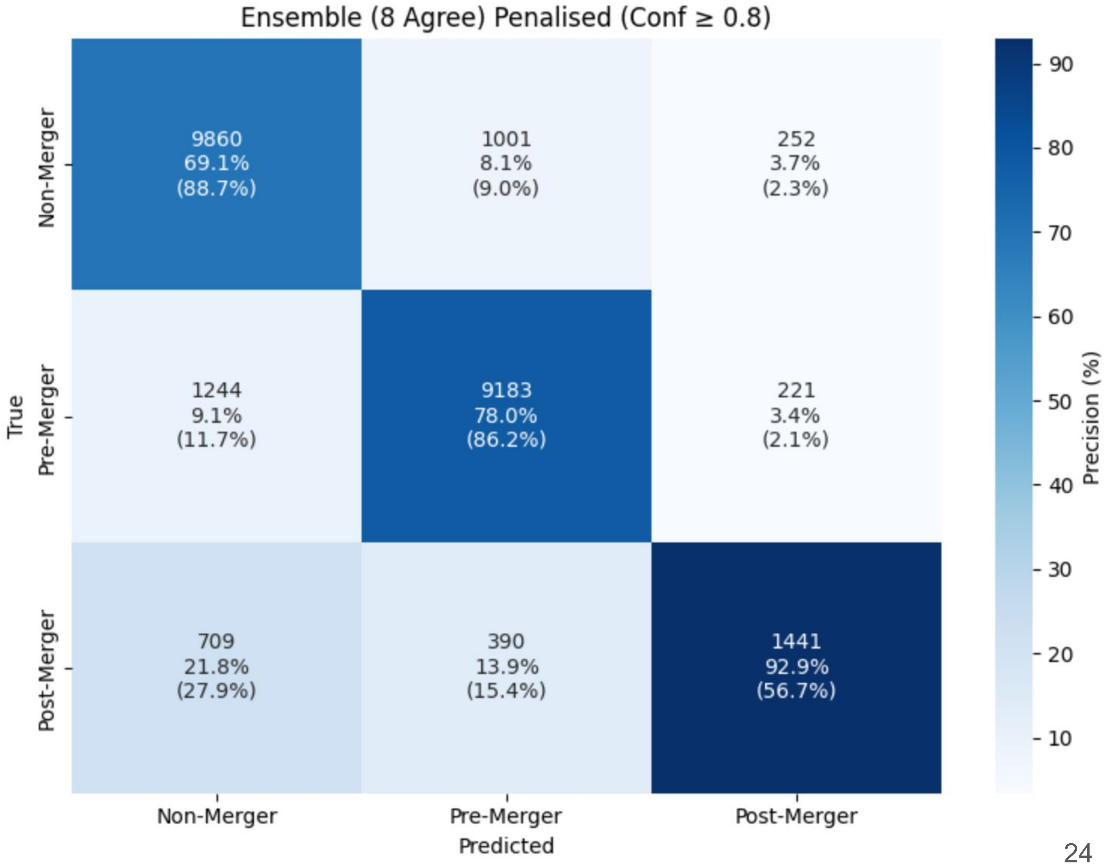
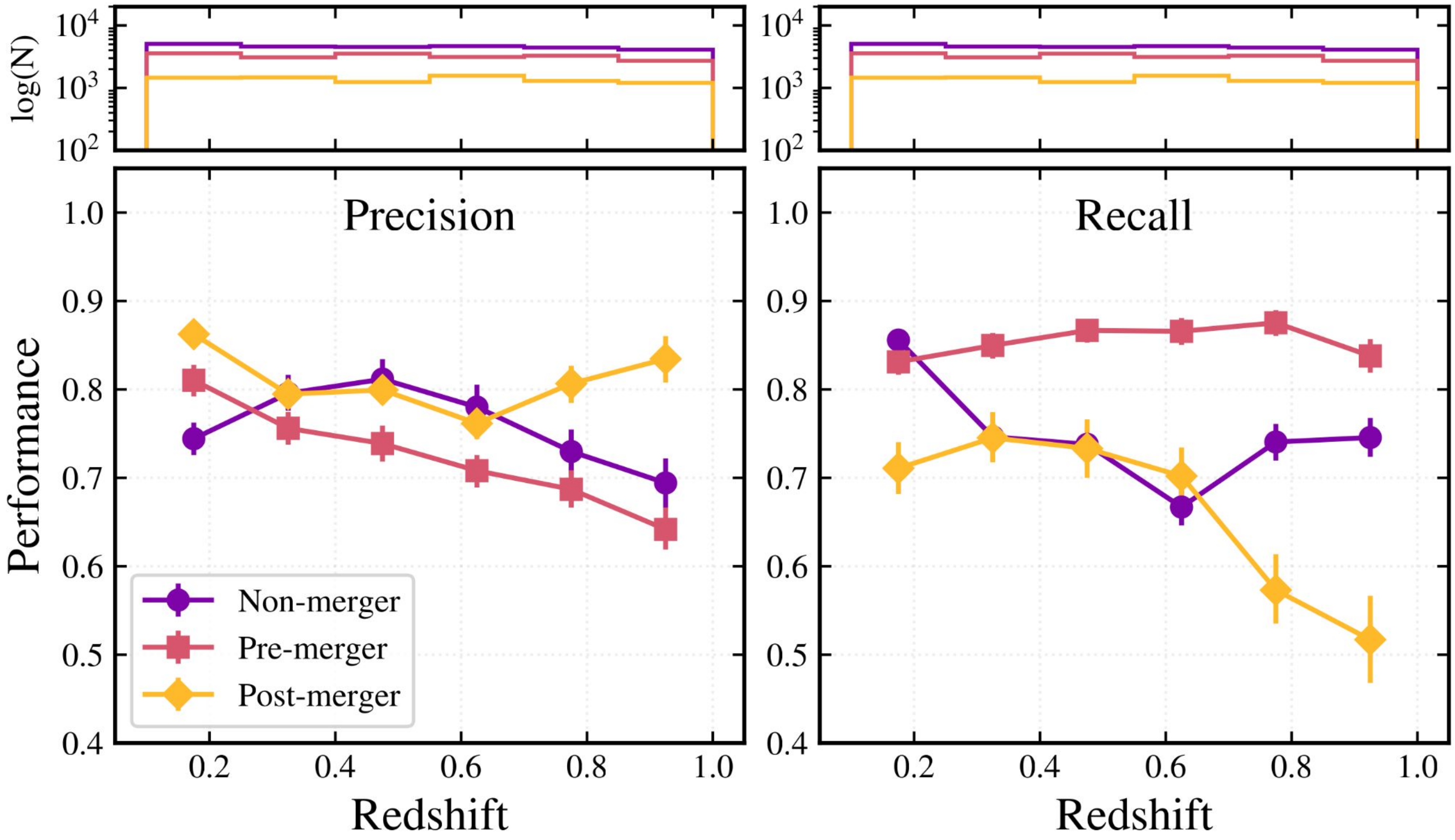
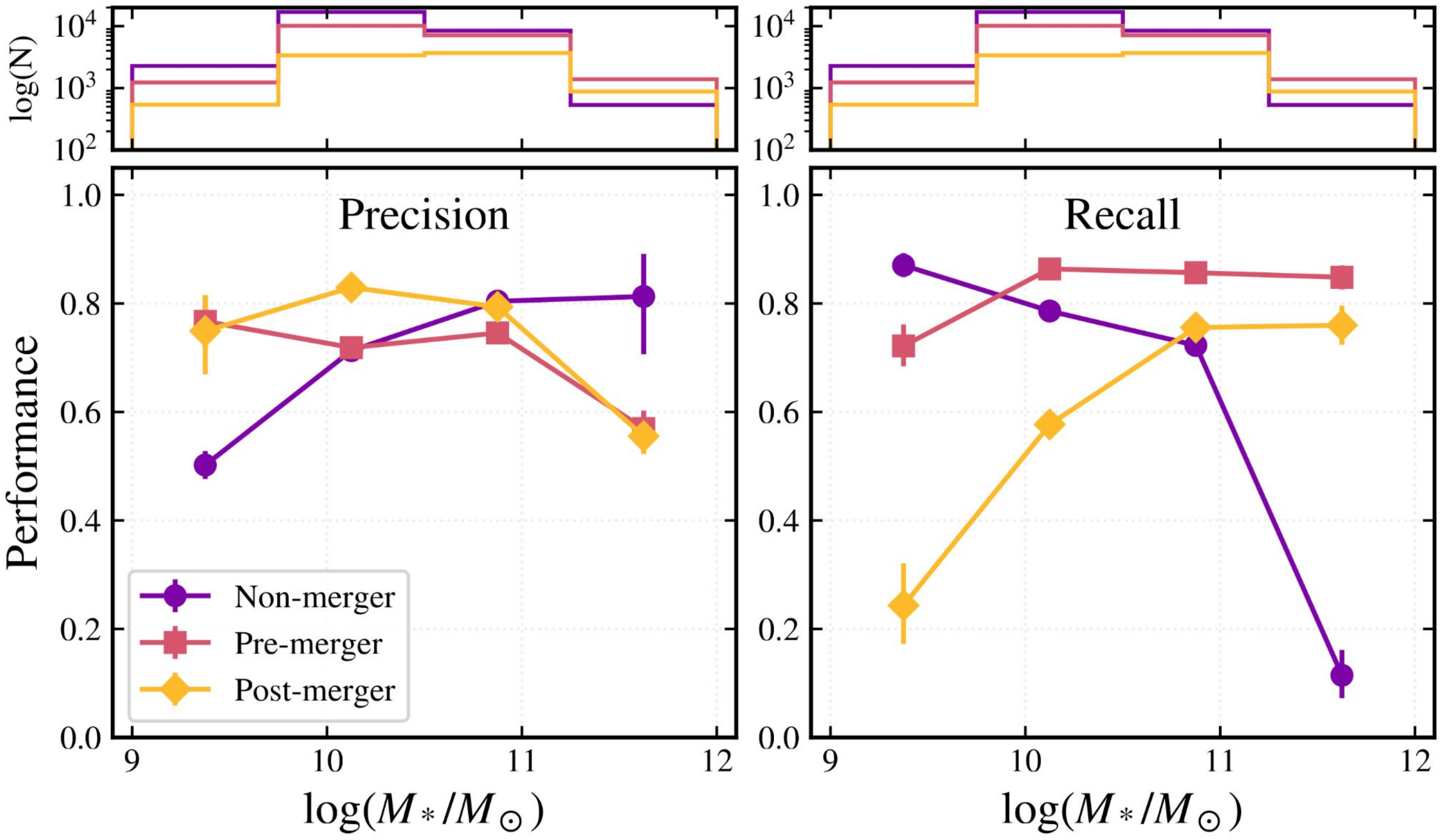




Ensemble performance vs redshift

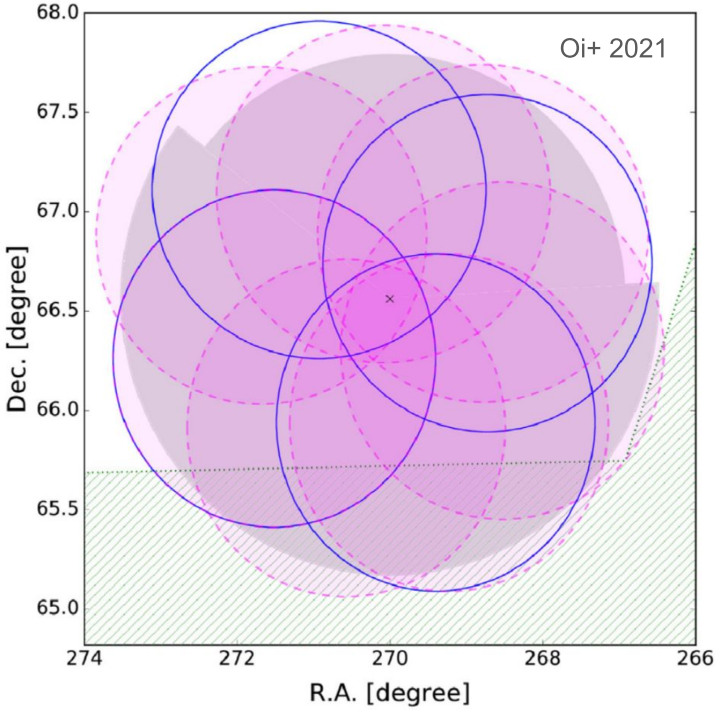


Ensemble performance vs mass

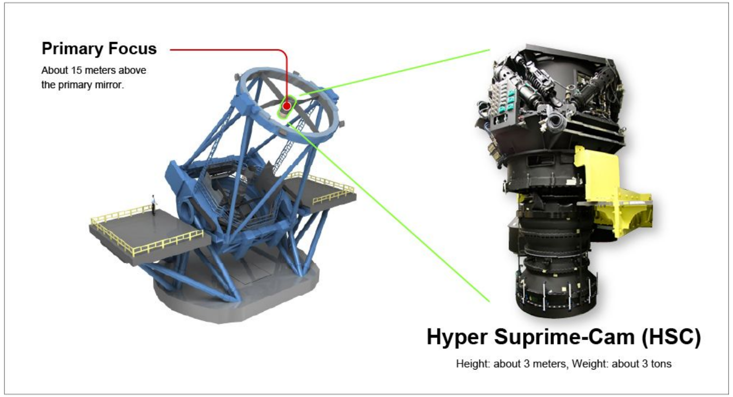


Moving from simulation to observations!

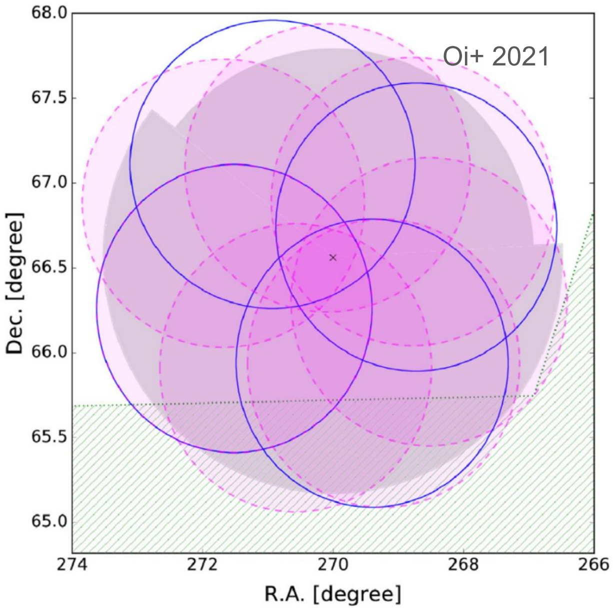
HSC observations of the AKARI-NEP field



Pink dashed–shadowed circles represent the HSC r-band observation area, while the four blue solid circles show the HSC g-, i-, z-, and y-band observation areas.



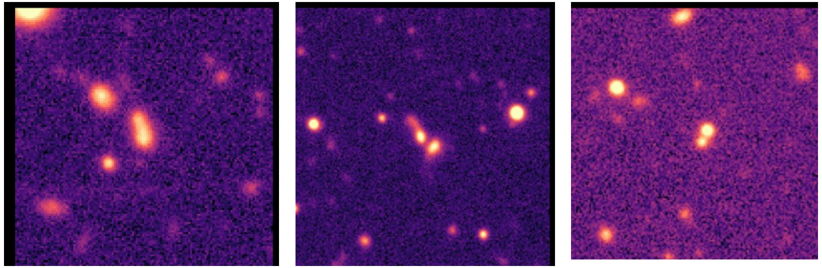
Merger predictions



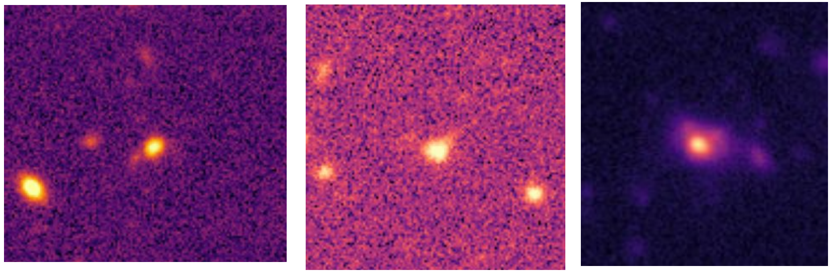
Prediction based on ensemble of networks

Total Galaxies	Non-merger	Pre-mergers	Post-mergers
287,984	253,066	28,387	6,601

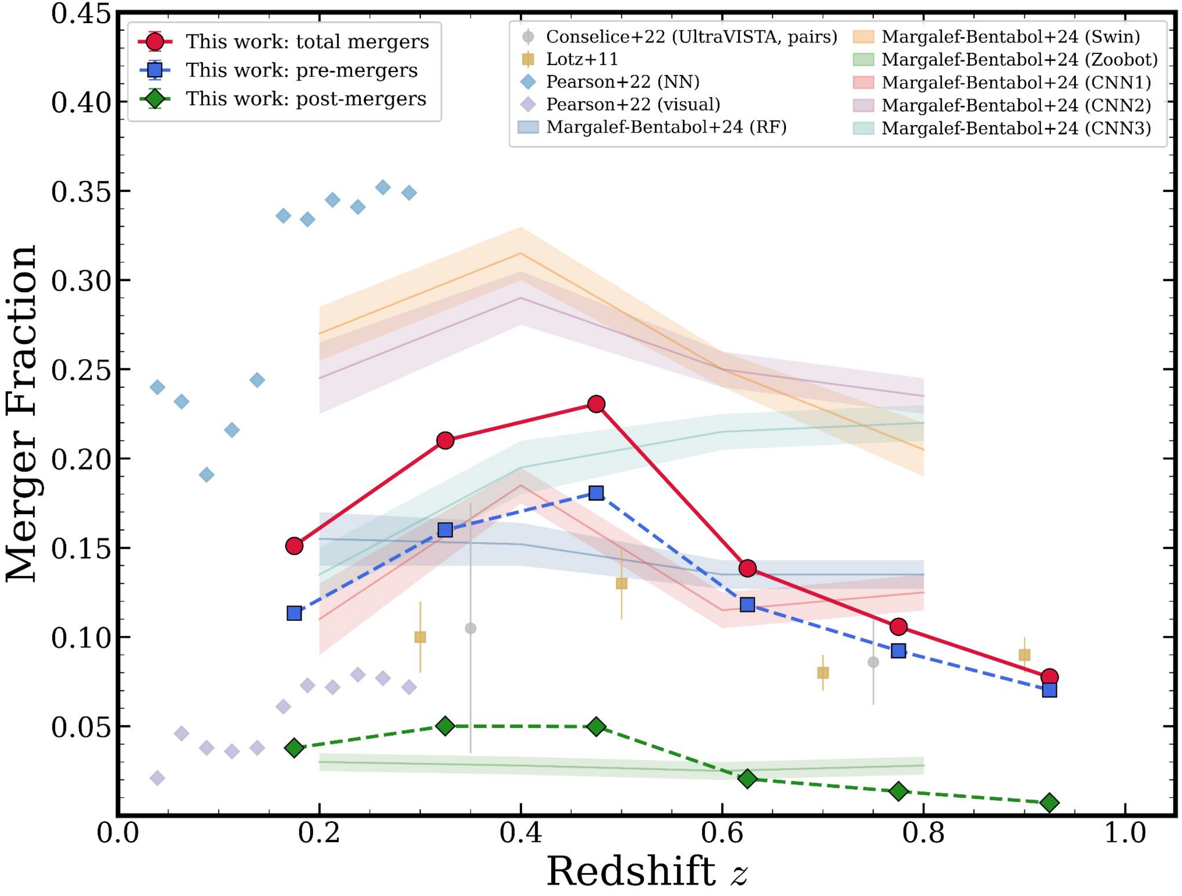
Pre-mergers



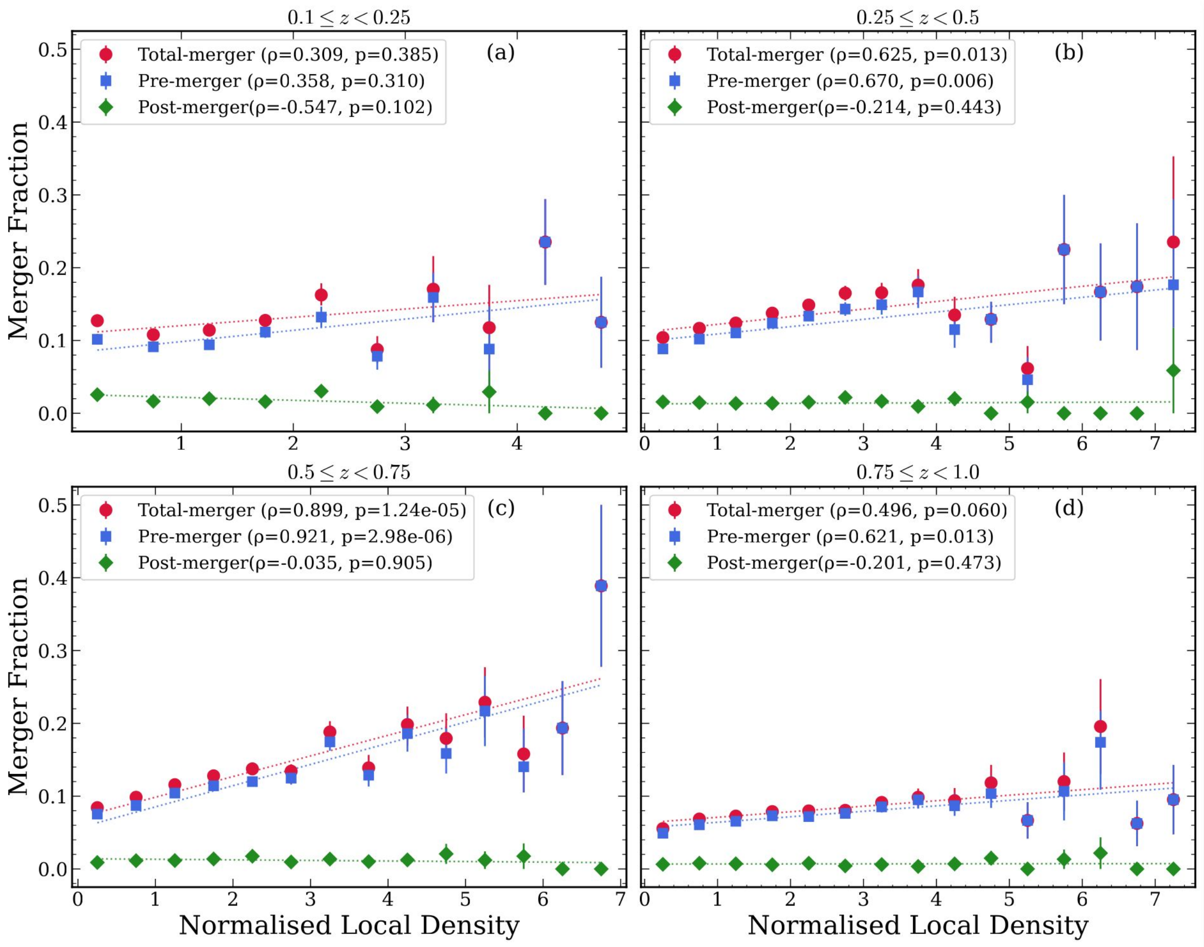
Post-mergers



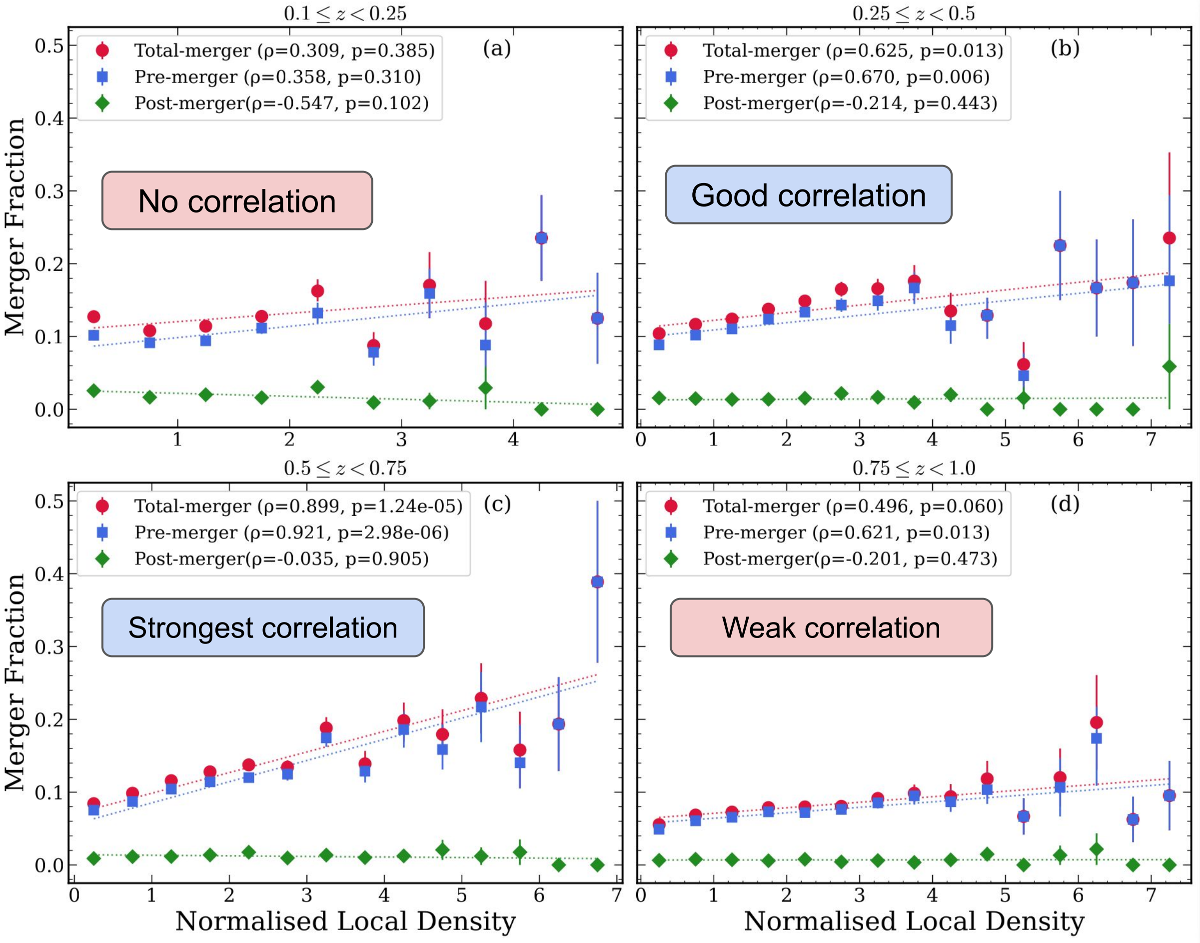
Merger fraction versus redshift



Merger fraction versus normalised local density



Merger fraction versus normalised local density



Pre-mergers show strong density correlation (ρ = 0.67–0.92, $p < 0.01$), peaking at z = 0.5–0.75

=> Preferentially occur in intermediate-density environments (groups and cluster outskirts) where density + low velocities maximize gravitational capture

Post-mergers show no significant dependence on local density at any redshift !!

=> Post-merger remnants can migrate within their environments and lose the original density signature

Summary

- ★ **Ensemble of 8 deep-learning networks** achieved the best merger-stage classification performance.
- ★ Classification performance is **strongly mass-dependent,** with significant variations in recall across stellar mass ranges.
- ★ **Merger fraction peaks at intermediate redshift ($z \approx 0.4–0.5$) and declines toward higher redshift.**
- ★ **Merger fraction shows a clear positive correlation with local density.**
- ★ **Pre-mergers dominate the merger population** and largely drive the observed redshift and environmental trends.
- ★ **Post-mergers remain relatively rare** and show weaker environmental dependence, suggesting shorter-lived observable signatures after coalescence.

Thank You :)

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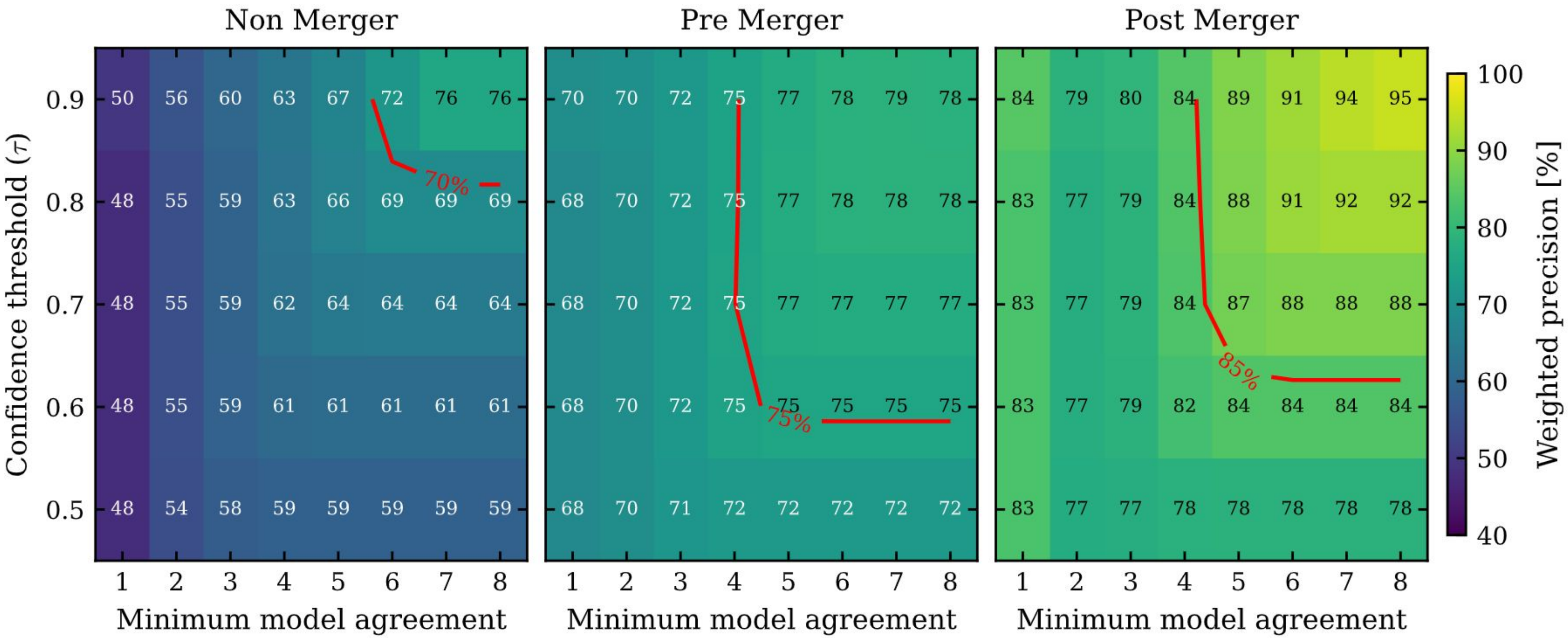
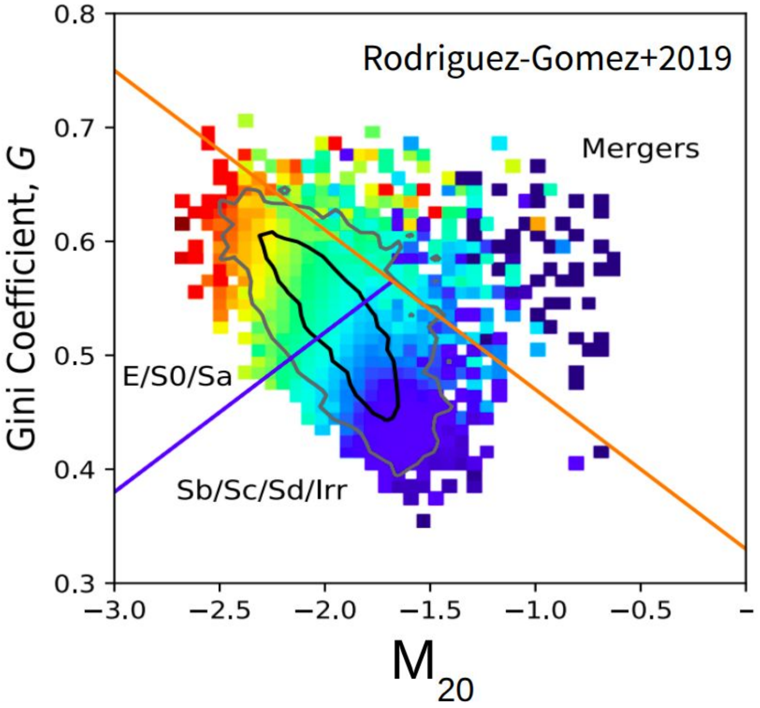

Non Merger
Pre Merger
Post Merger
Confidence threshold (τ)
Minimum model agreement
Weighted precision [%]
70%
75%
85%
0.9: 50 56 60 63 67 72 76 76 | 70 70 72 75 77 78 79 78 | 84 79 80 84 89 91 94 95
0.8: 48 55 59 63 66 69 69 69 | 68 70 72 75 77 78 78 78 | 83 77 79 84 88 91 92 92
0.7: 48 55 59 62 64 64 64 64 | 68 70 72 75 77 77 77 77 | 83 77 79 84 87 88 88 88
0.6: 48 55 59 61 61 61 61 61 | 68 70 72 75 75 75 75 75 | 83 77 79 82 84 84 84 84
0.5: 48 54 58 59 59 59 59 59 | 68 70 71 72 72 72 72 72 | 83 77 77 78 78 78 78 78
1 2 3 4 5 6 7 8
40 50 60 70 80 90 100

Morphological statistics



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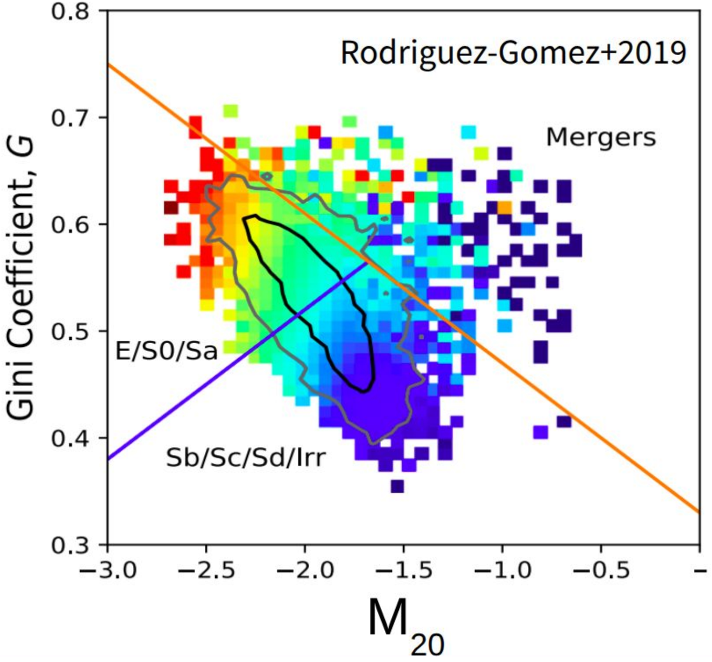
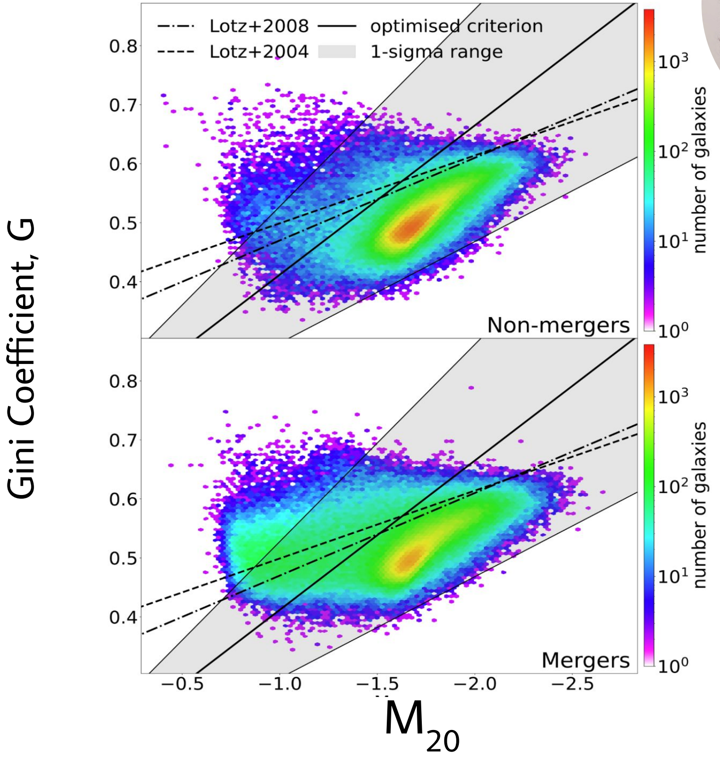




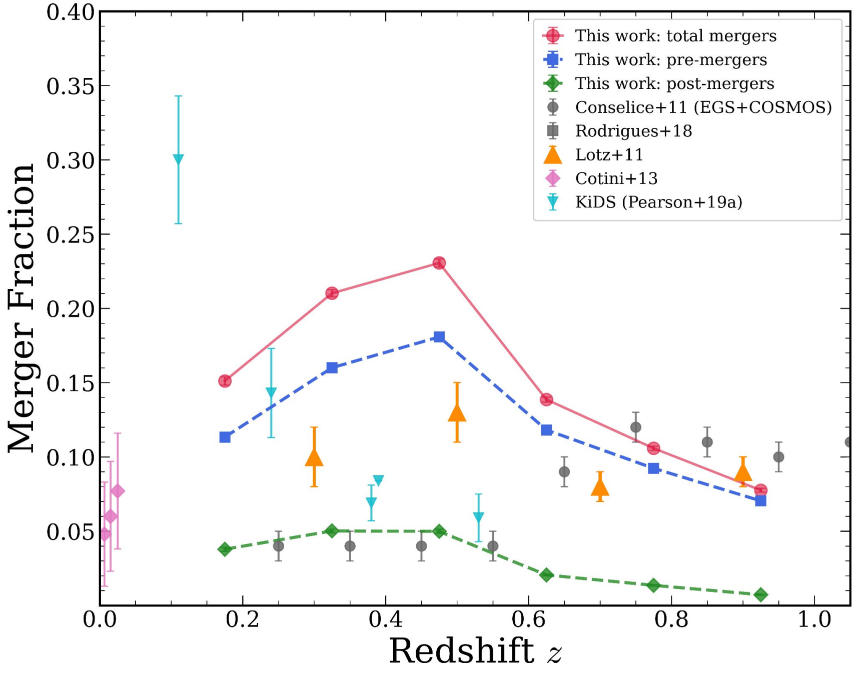
Lotz et al. 2008

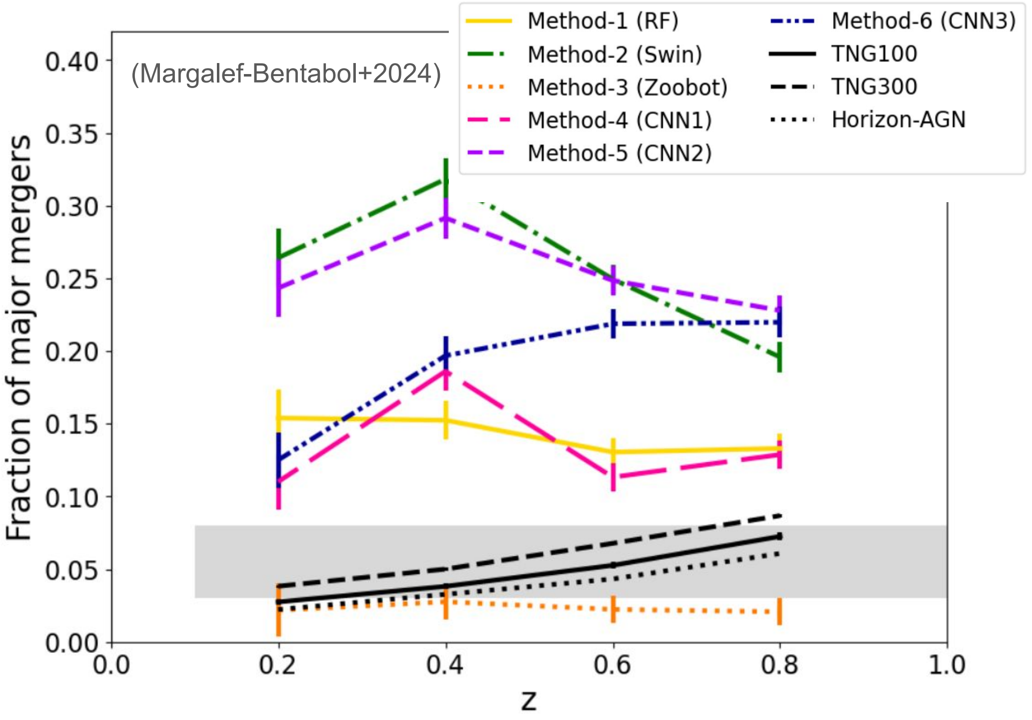
$G > -0.14\ M_{20} + 0.33$

Cotter et al. (2026)

$G > (-0.253 \pm 0.081)\ M_{20} + (0.159 \pm 0.035)$

Merger fraction versus redshift



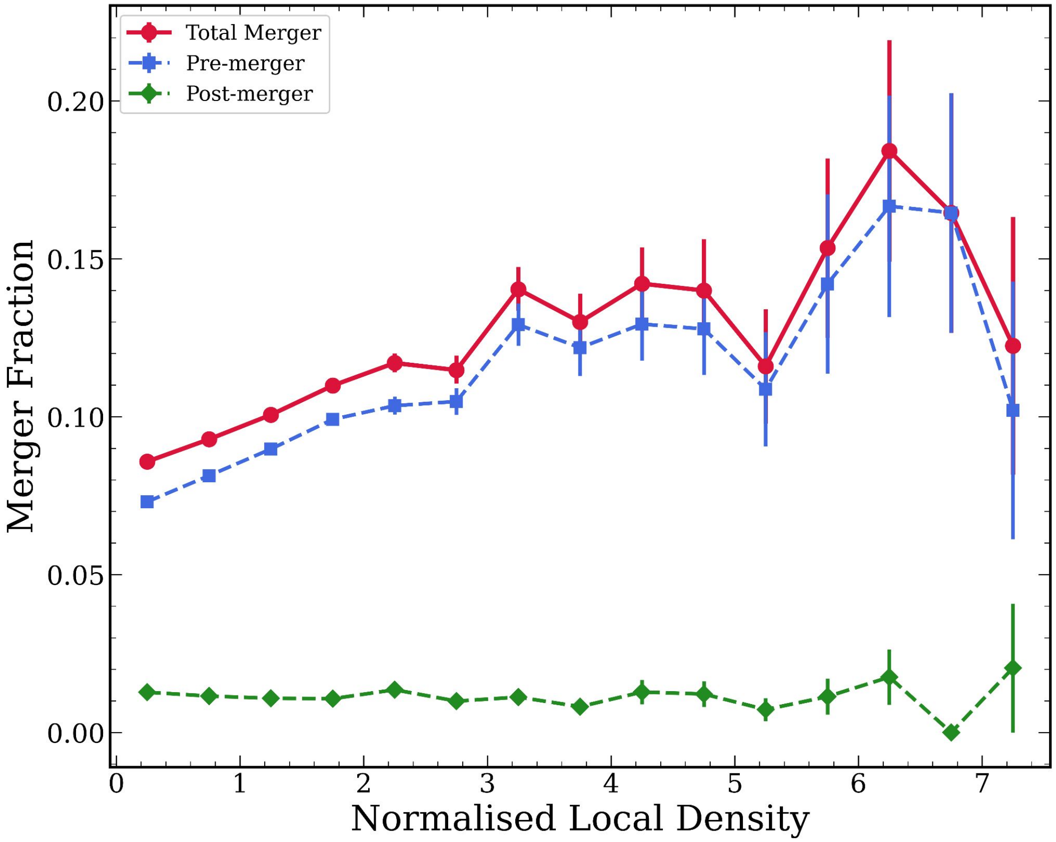


observational limit! As we go to higher redshifts, the images become fainter, making it harder for a DL network to 'see' the merger signatures.

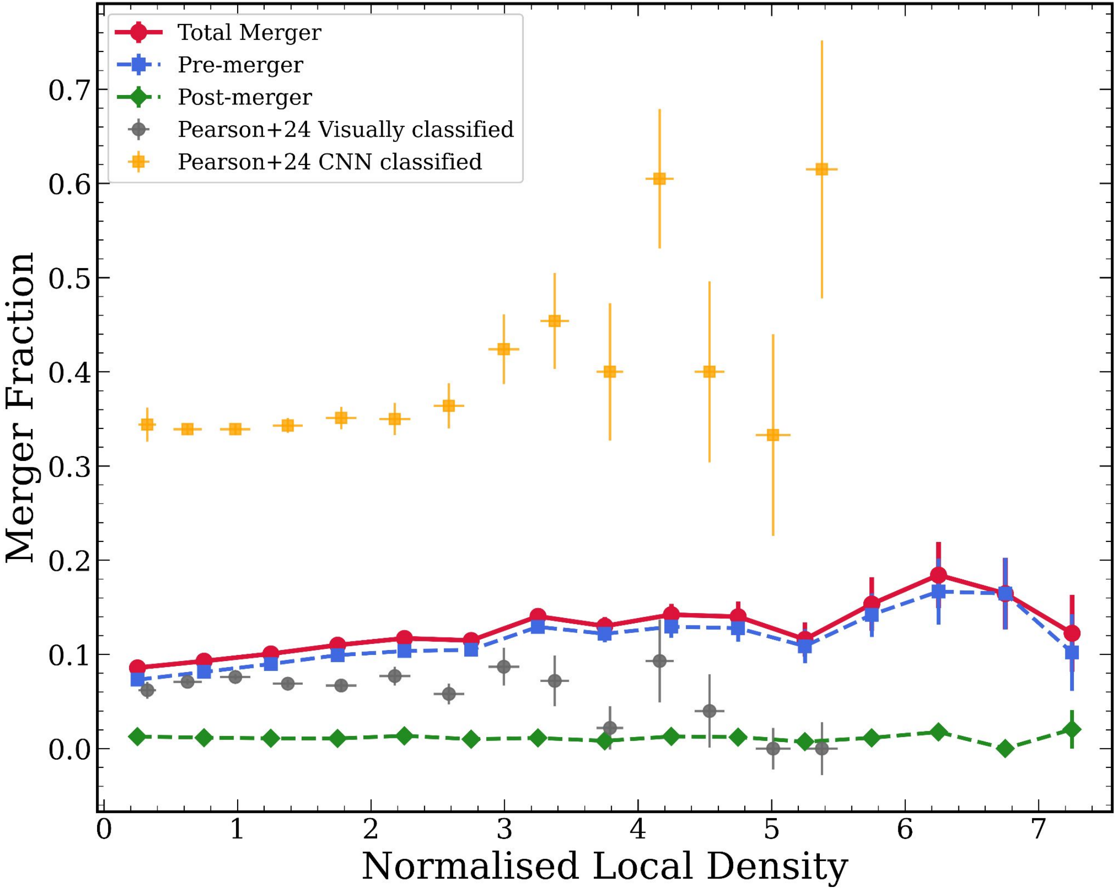
Merger fraction versus normalised local density

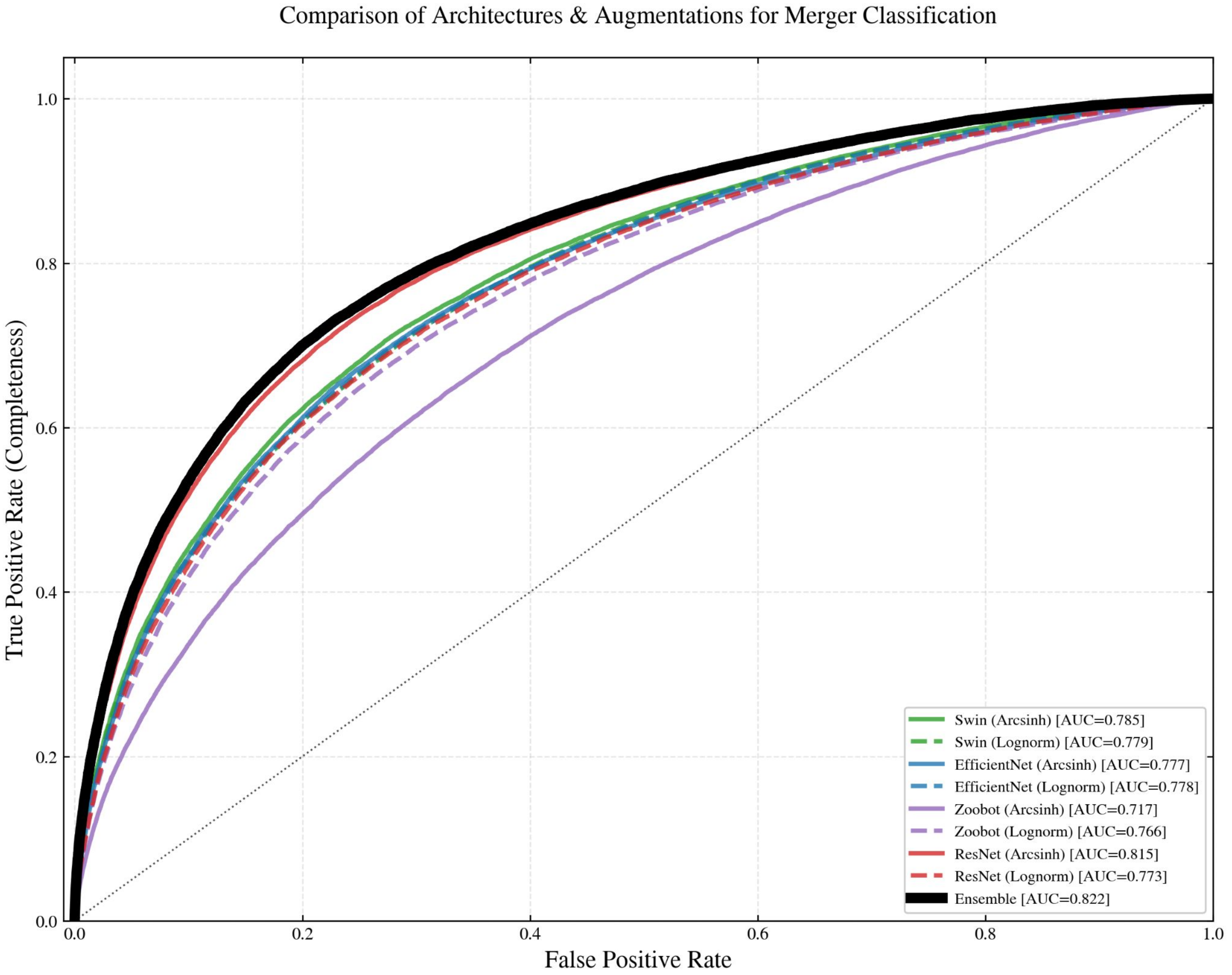
Local densities : 10th nearest neighbour in 2-dimensions using only galaxies within a redshift bin of width $0.065 \times (1 + z)$ (Santos+ 21)

Galaxies in denser environments have a higher probability of interacting.



Merger fraction versus local density

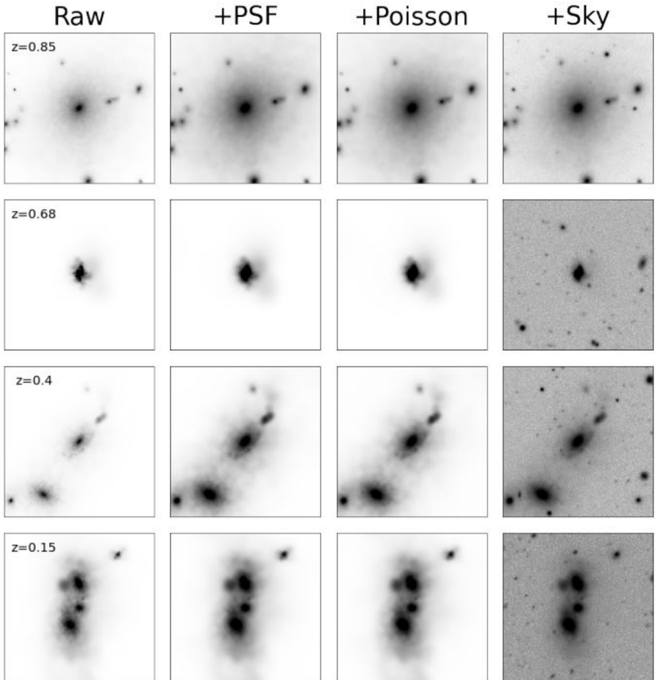




Comparison of Architectures & Augmentations for Merger Classification
True Positive Rate (Completeness)
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Swin (Arcsinh) [AUC=0.785]
Swin (Lognorm) [AUC=0.779]
EfficientNet (Arcsinh) [AUC=0.777]
EfficientNet (Lognorm) [AUC=0.778]
Zoobot (Arcsinh) [AUC=0.717]
Zoobot (Lognorm) [AUC=0.766]
ResNet (Arcsinh) [AUC=0.815]
ResNet (Lognorm) [AUC=0.773]
Ensemble [AUC=0.822]

Workflow for Galaxy Merger Classification

Acquire Mock HSC Images



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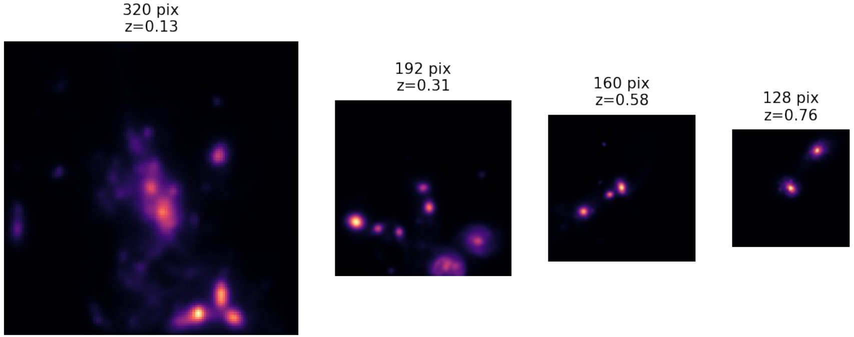
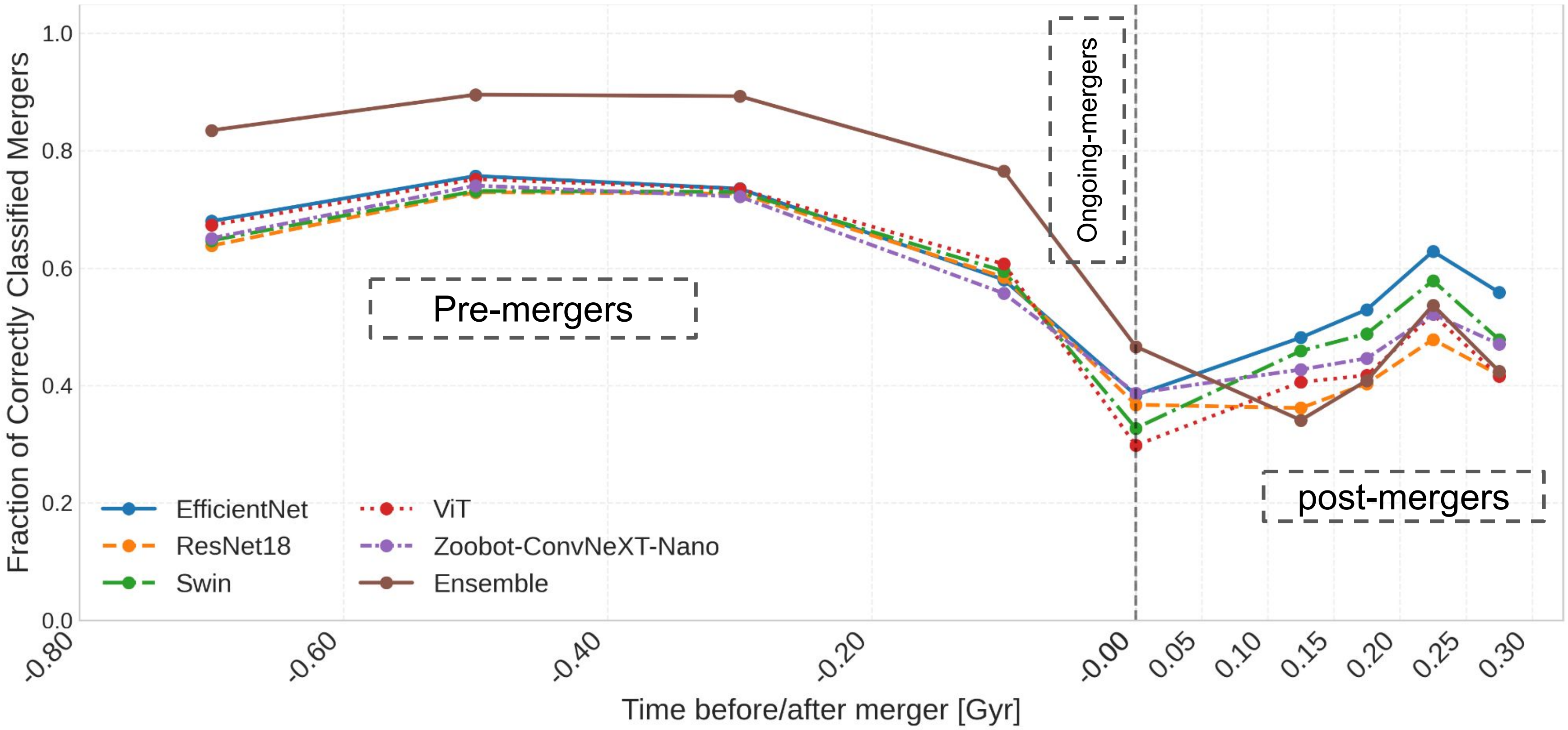
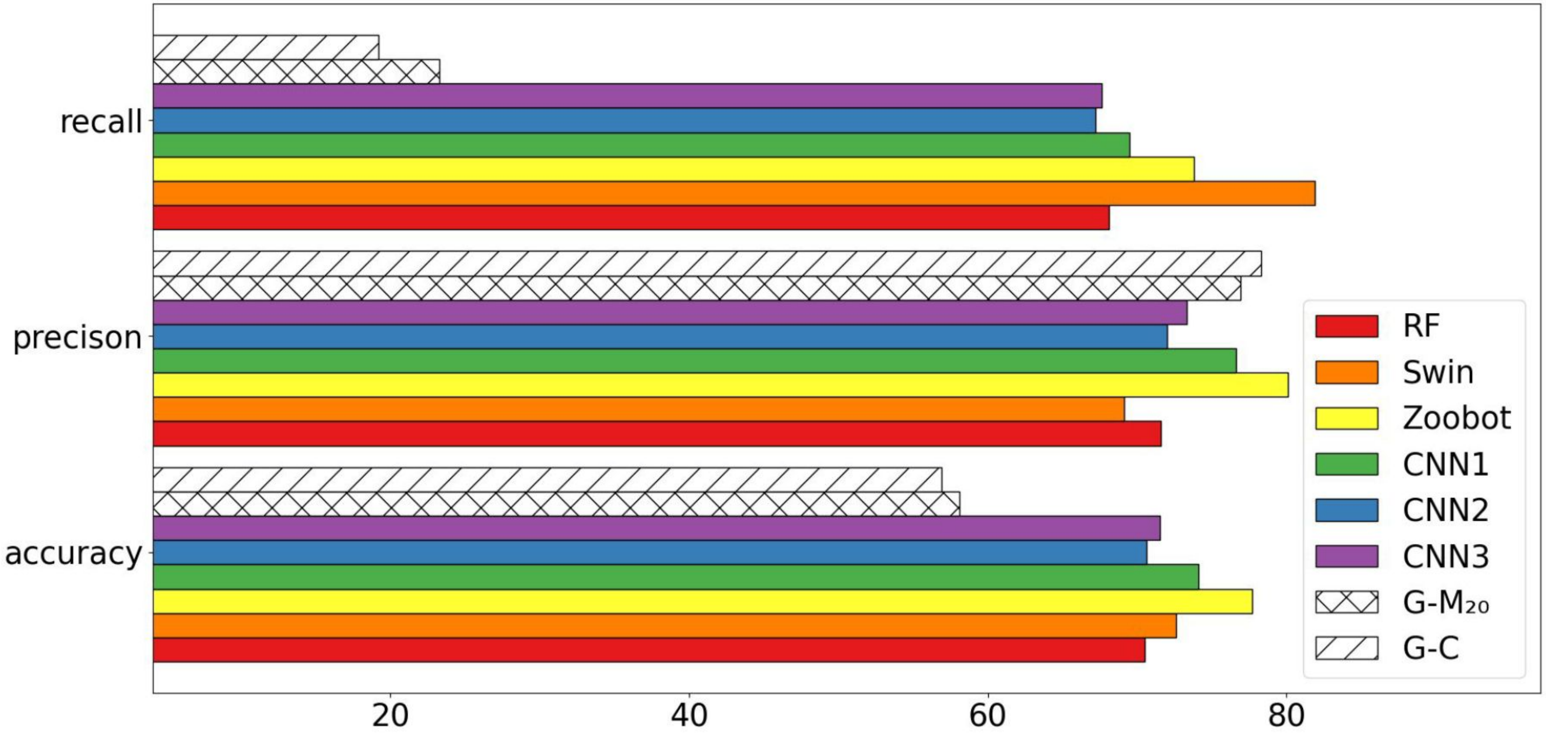


z= 0.10–0.31 | 0.31–0.52 | 0.52–0.76 | 0.76–1.00

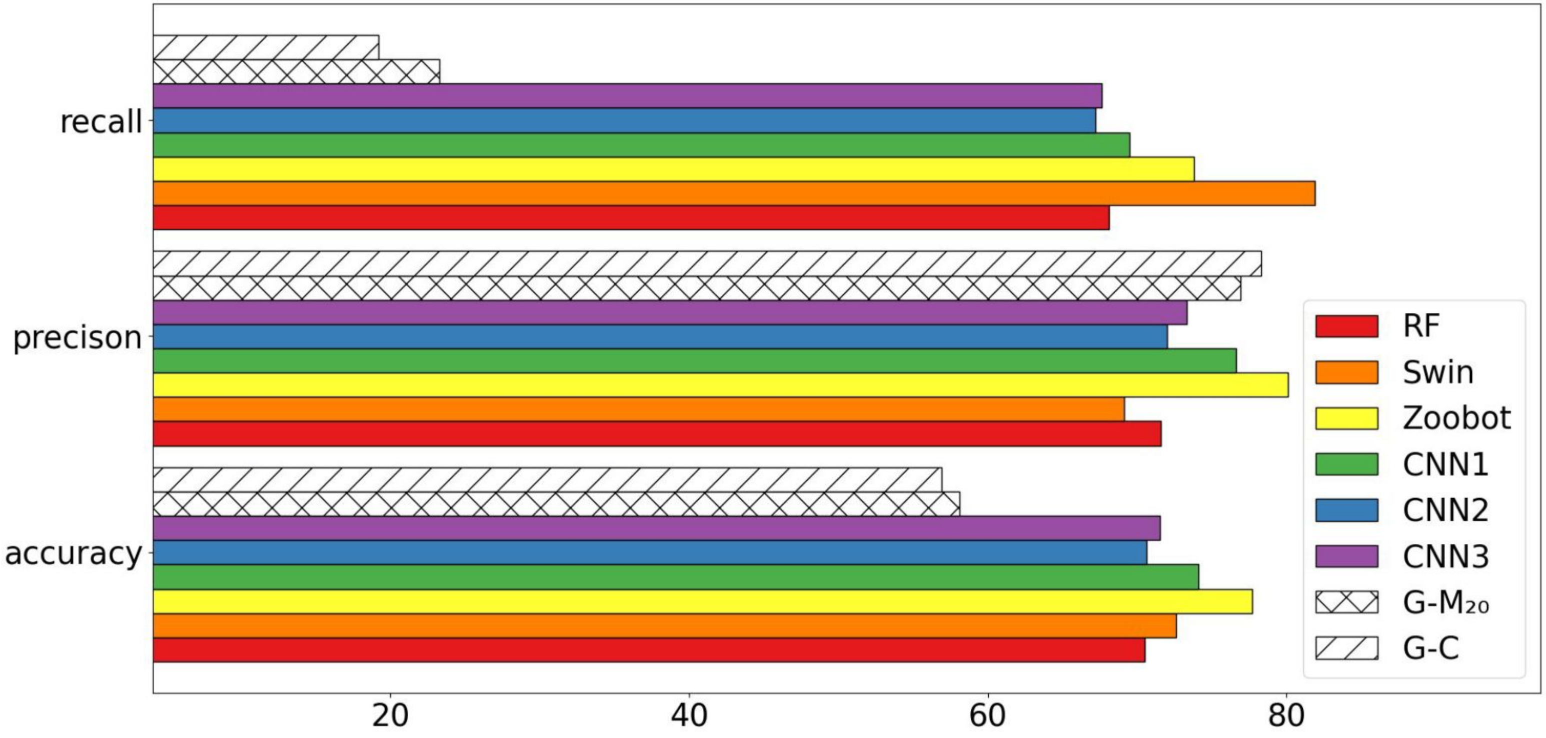
Fraction of correctly classified Mergers vs Merger times



Morphological statistics

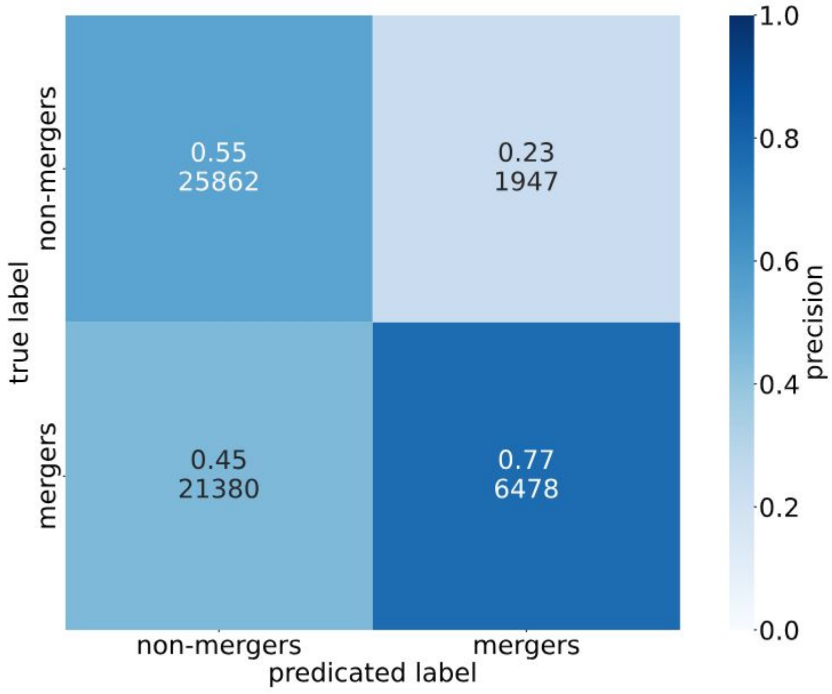


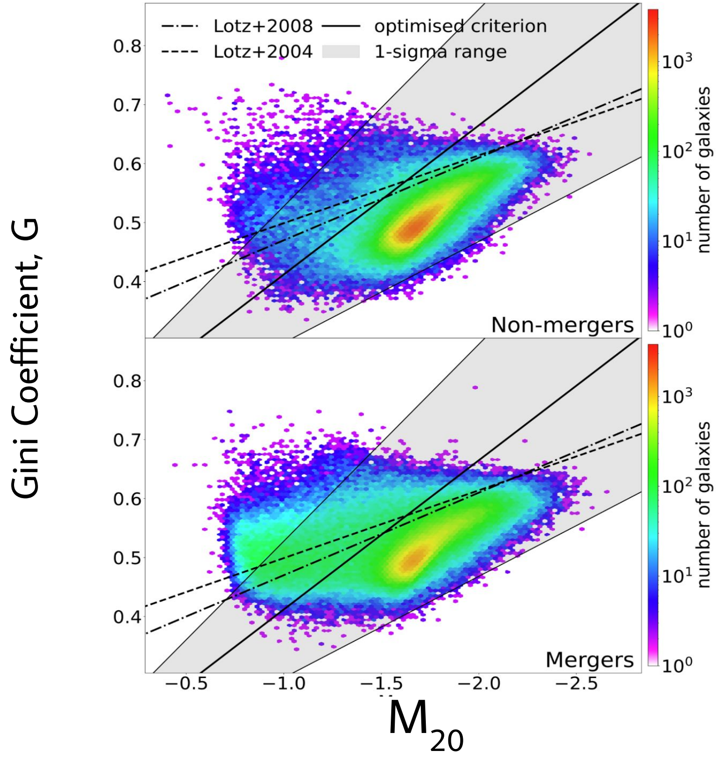
Morphological statistics



Morphological classifiers can be as precise as machine learning (>75%)

Morphological statistics



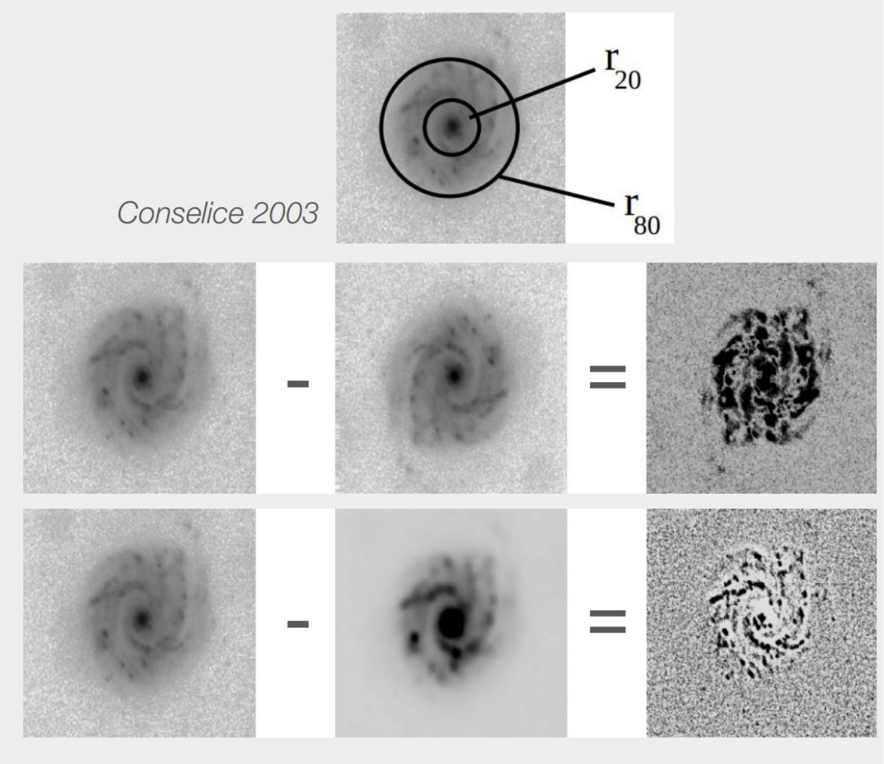


Cotter et al. (in prep)

$G > (-0.253 \pm 0.081)\, M_{20} + (0.159 \pm 0.035)$

Morphology parameters

CAS System



Concentration:

1. Find radii enclosing 20% and 80% of the light (r_{20}, r_{80})
2. Take ratio

Asymmetry:

1. Rotate image
2. Subtract from original
3. Sum pixel values

Smoothness:

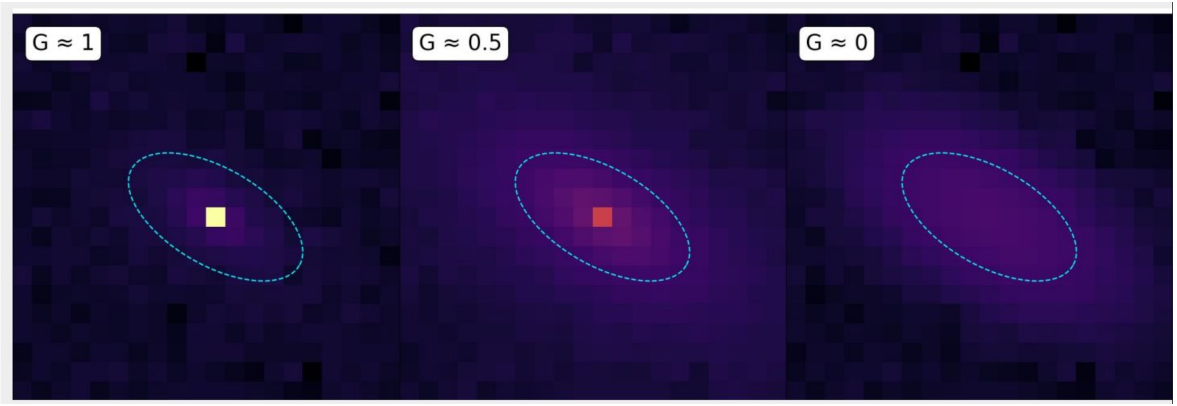
1. Smooth image
2. Subtract from original
3. Sum pixel values

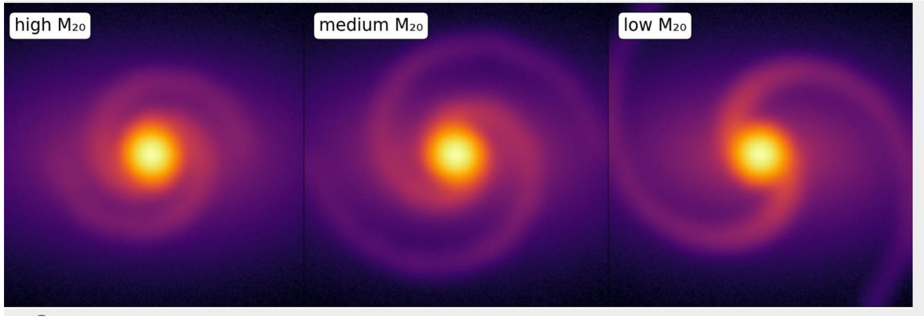
Slide Credit: Aidan Cotter

Morphology parameters

Gini-M20

Gini:
Borrowed econometric statistic
Describes inequality in pixel brightness





M20:
2nd order moment of the brightest 20%
Traces distribution of bright structures (eg. spiral arms, bars, clumps)

Slide Credit: Aidan Cotter