Deep learning approaches to galaxy merger identification and classification

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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?

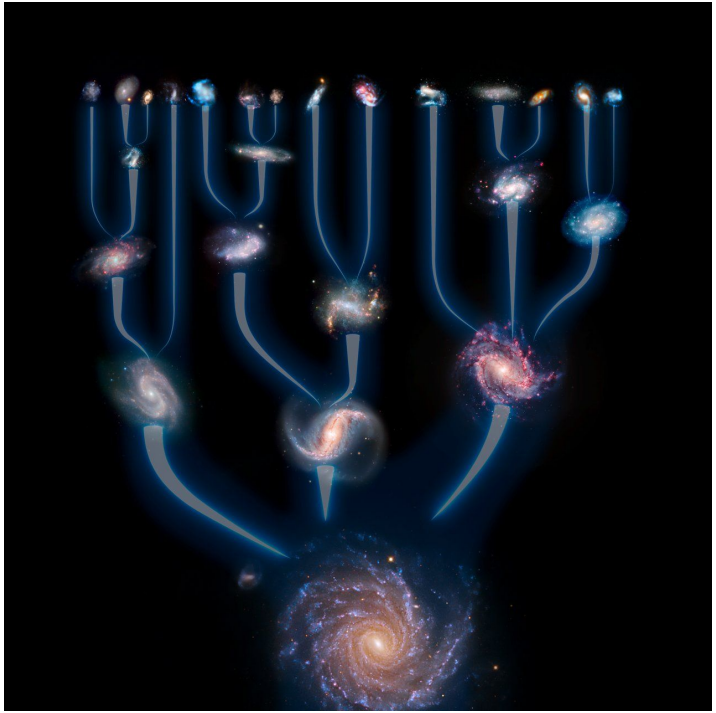


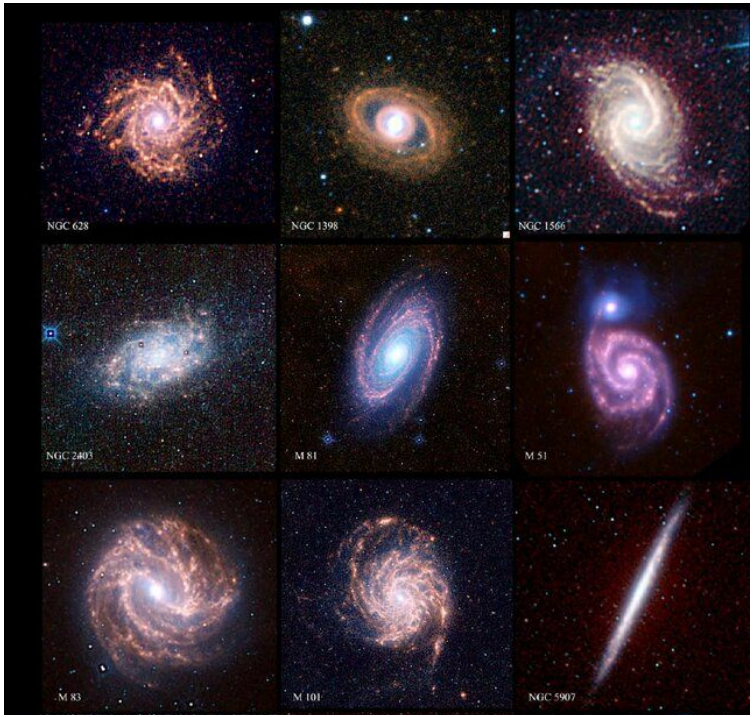
Image credit: ESO

- **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



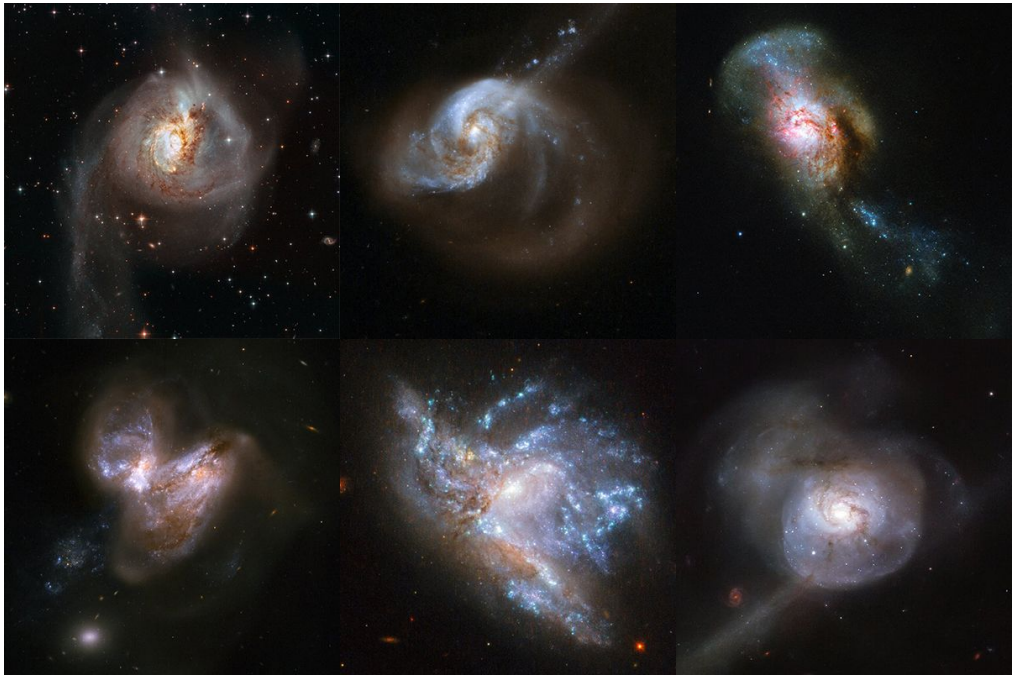
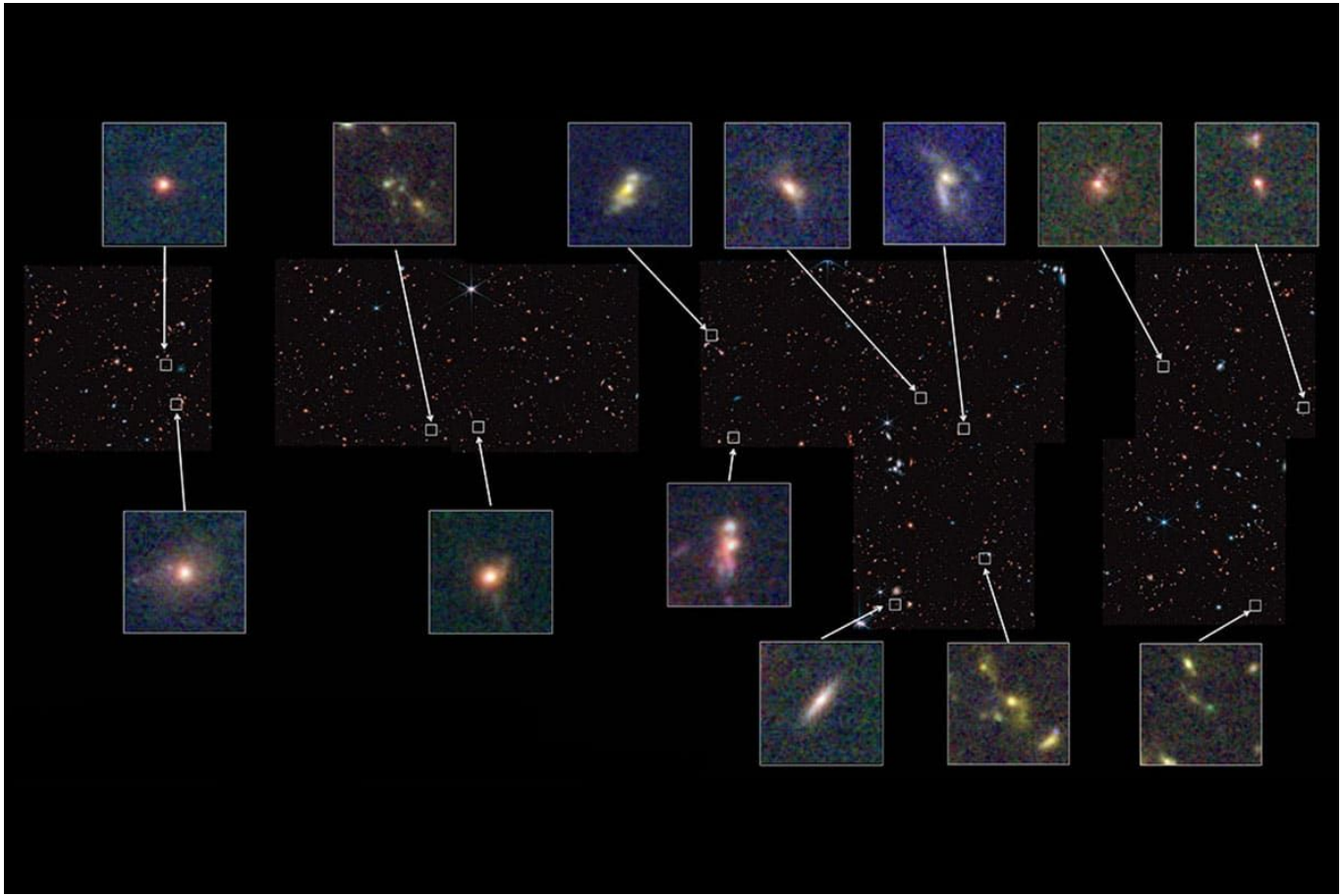


Image credit: ESA

Merger identification : Visual Classification

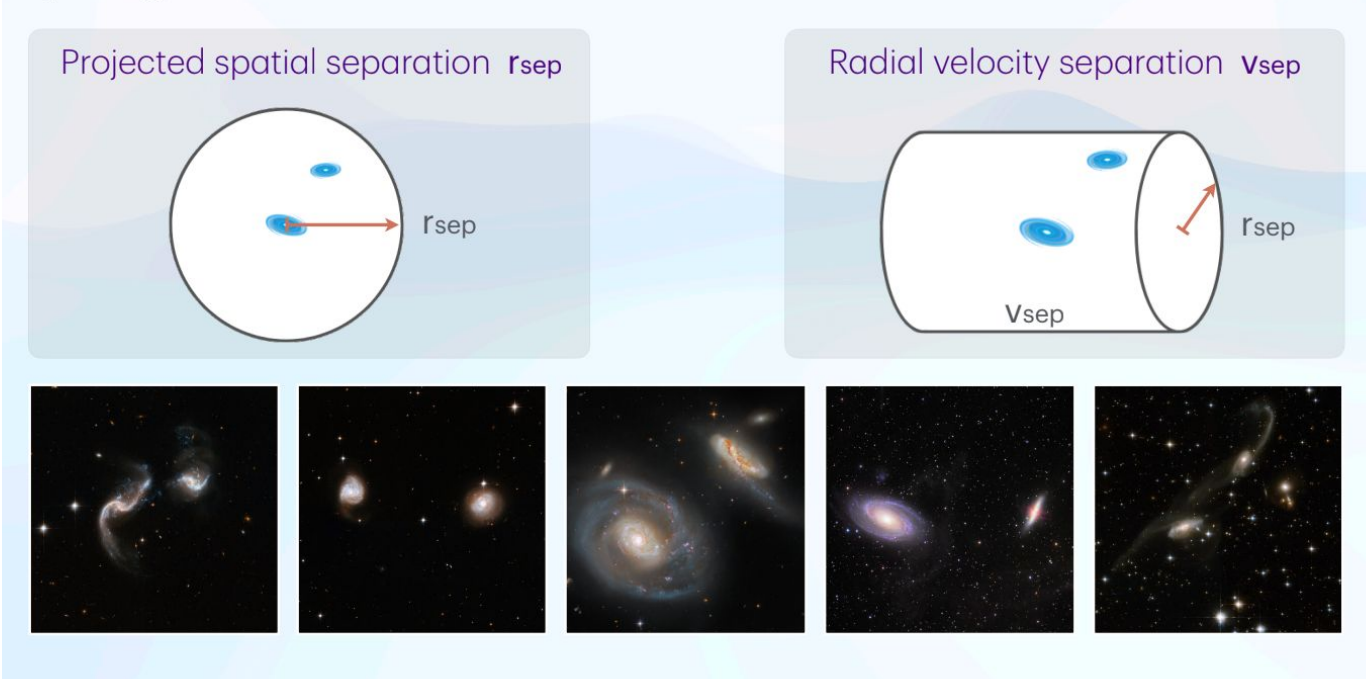


Merger identification : Close Pair

2

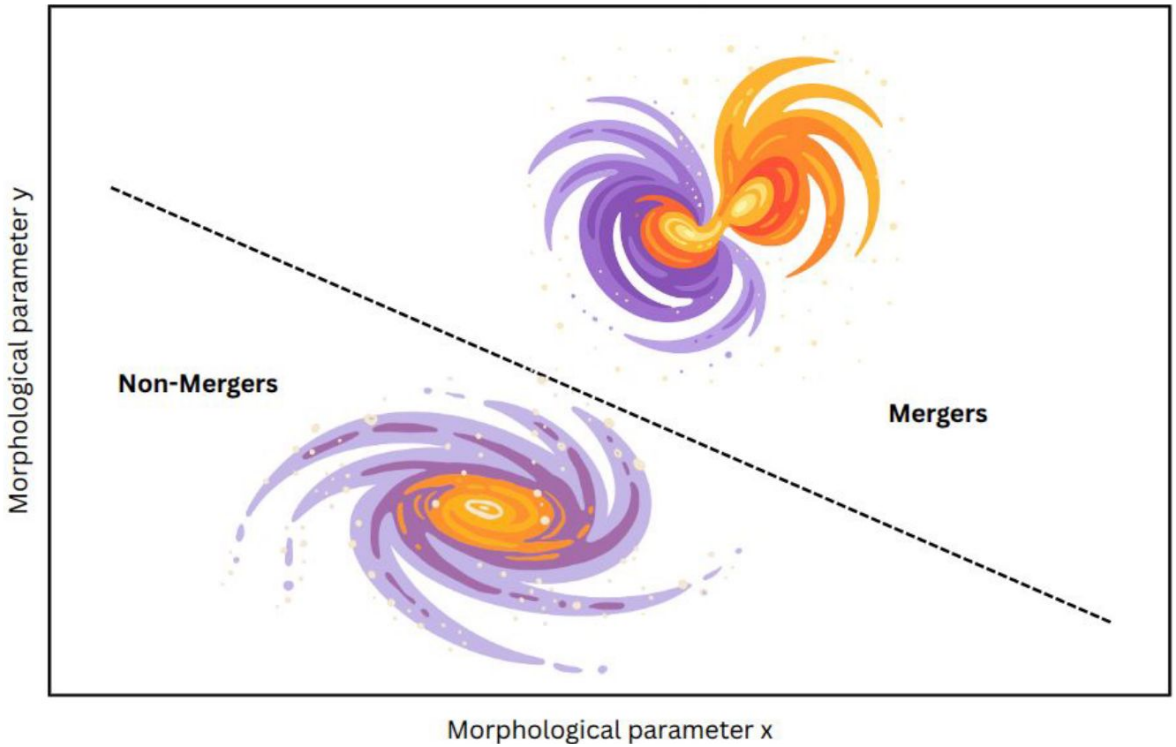
Galaxies close on the sky (< 20–50 kpc)

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



Merger identification: Morphological cuts

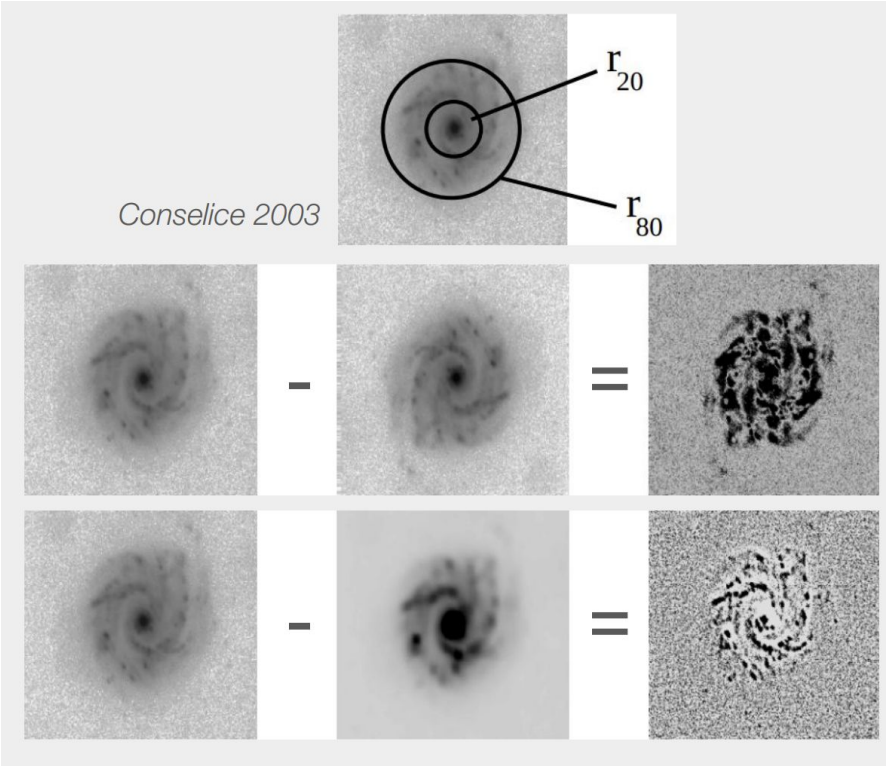
3



Slide Credit: Aidan Cotter

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:

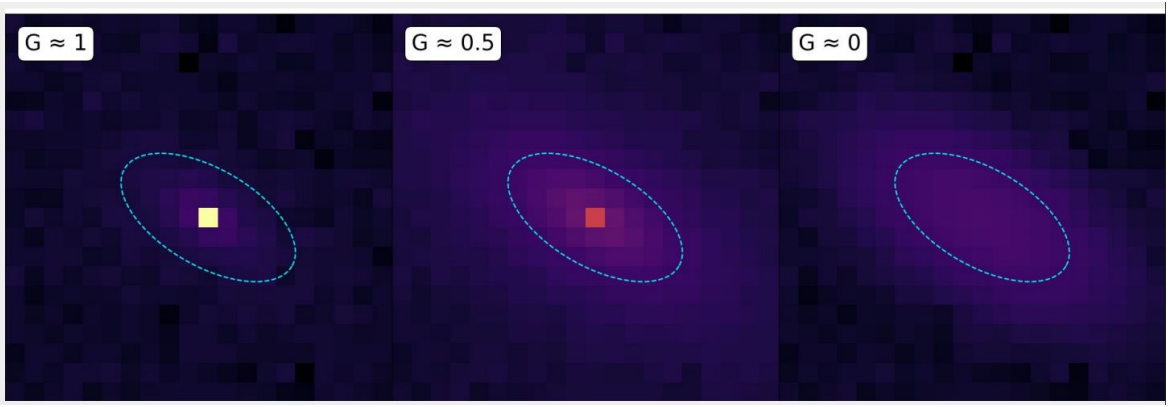
1. Smooth image
2. Subtract from original
3. Sum pixel values

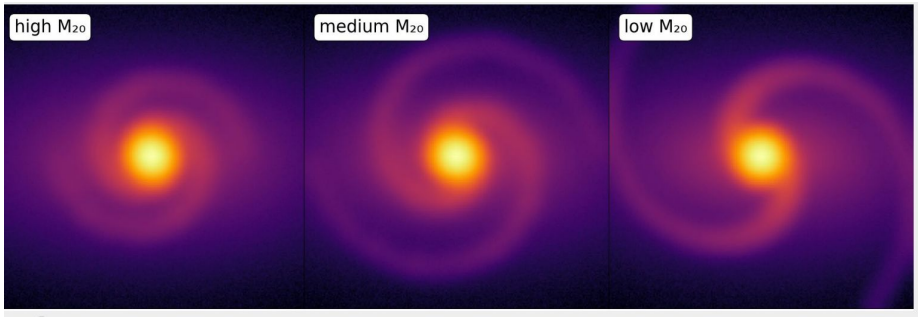
Slide Credit: Aidan Cotter

Morphology parameters

Gini-M20

Gini:
Borrowed econometric statistic
Describes inequality in pixel brightness

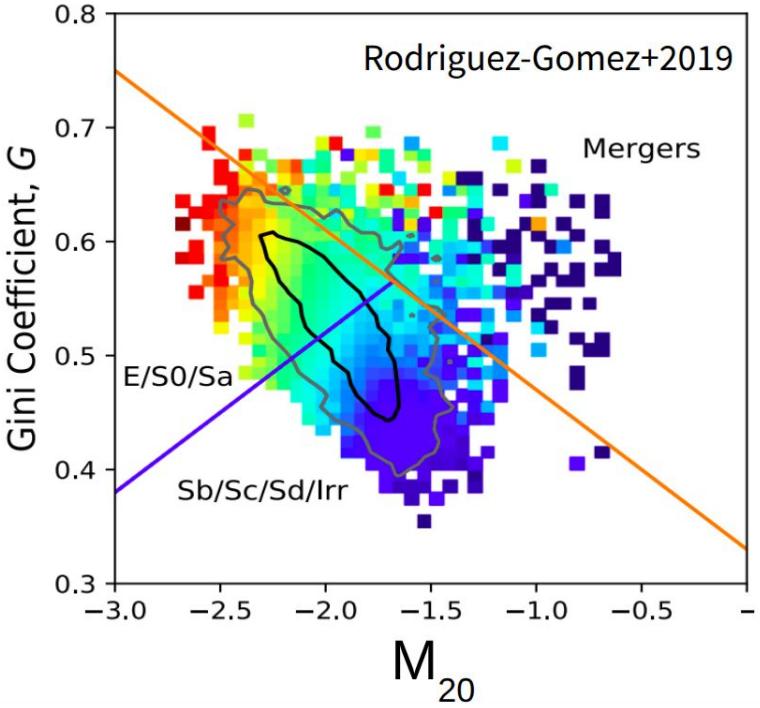




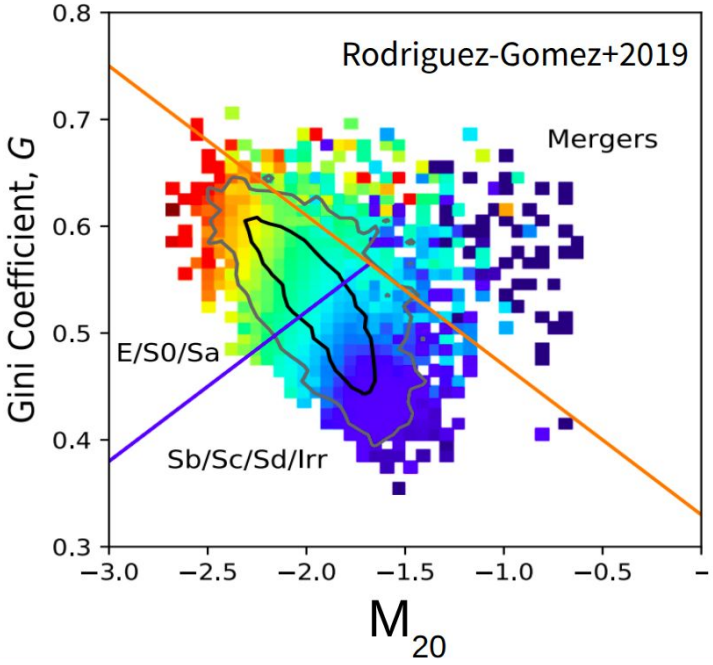
M20:
2nd order moment of the brightest 20%
Traces distribution of bright structures (eg. spiral arms, bars, clumps)

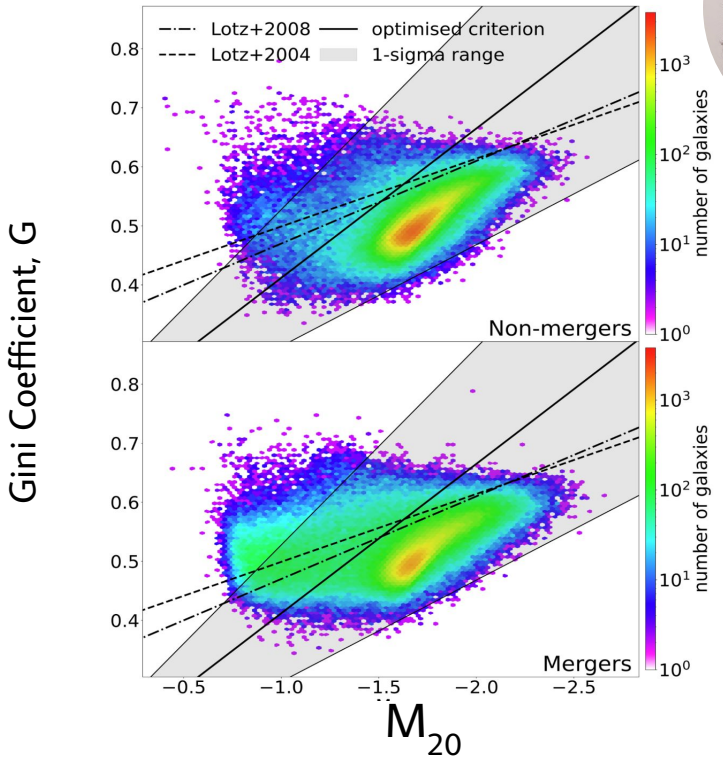
Slide Credit: Aidan Cotter

Morphological statistics



Morphological statistics





Lotz et al. 2008

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

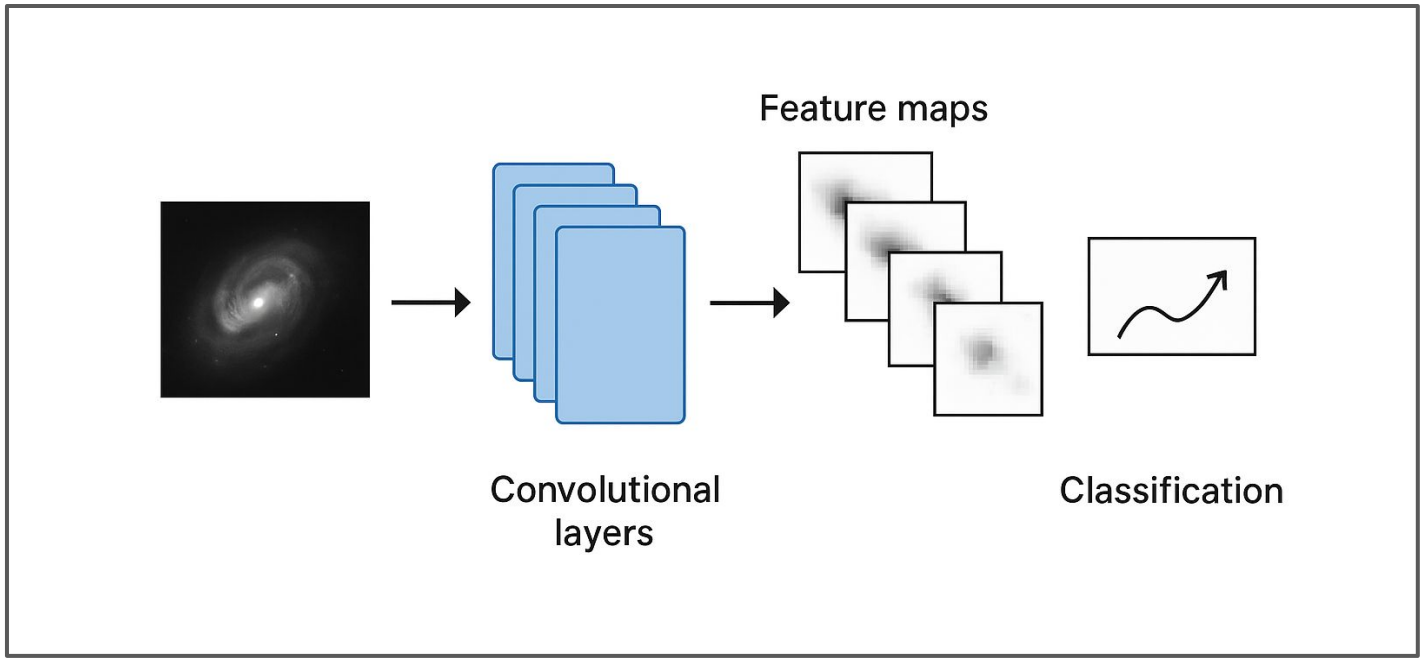
Cotter et al. (2026)

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

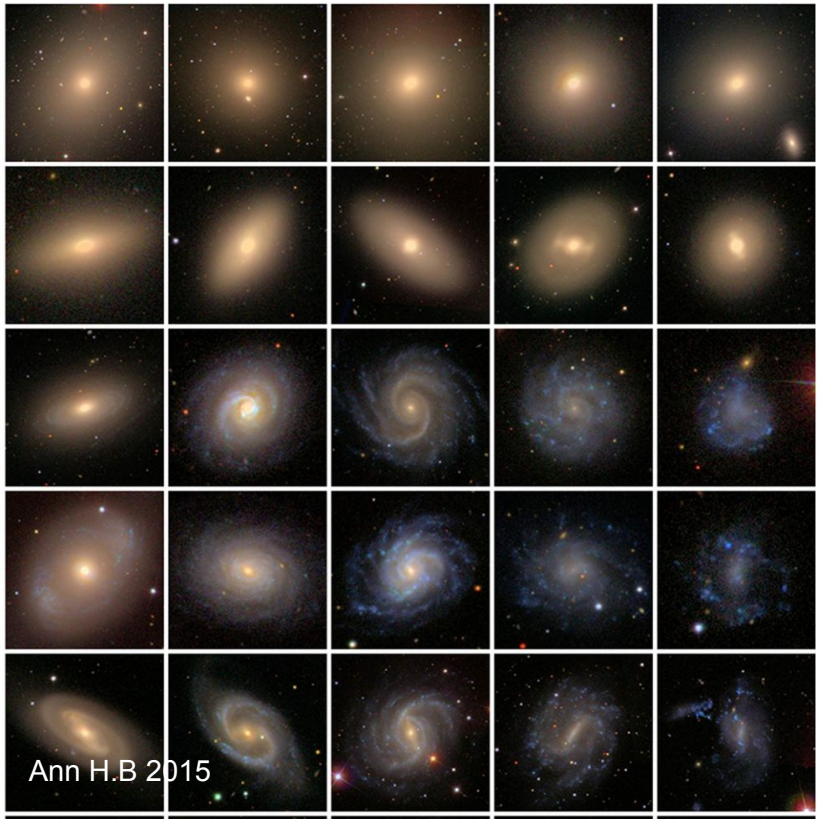
Merger identification : Deep learning

★ Powerful approach for automatically classifying galaxy mergers from imaging data

★ It learn patterns from data, making it ideal for complex tasks like galaxy classification.

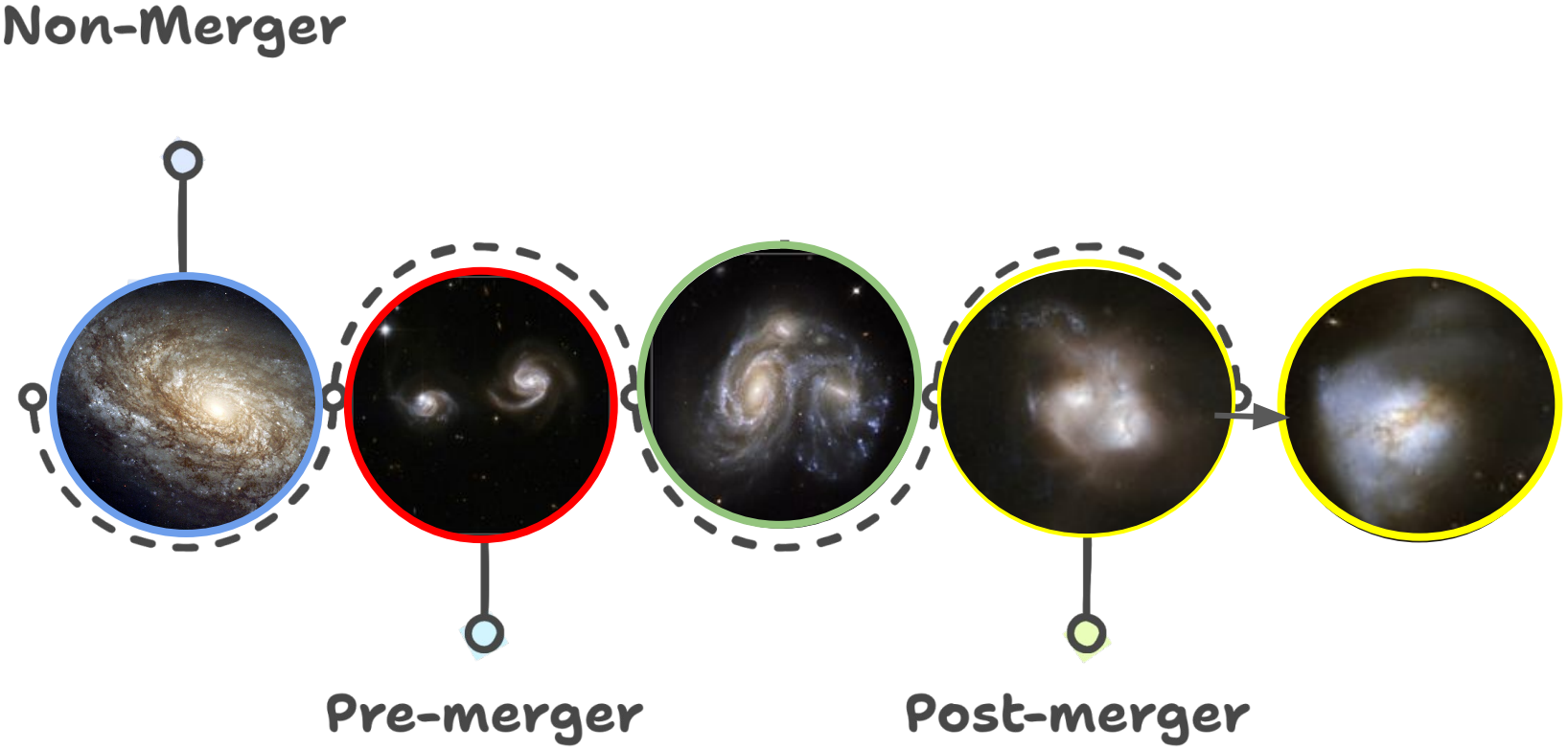


AIM: Going beyond merger / non-merger classification





AIM: Going beyond merger / non-merger classification



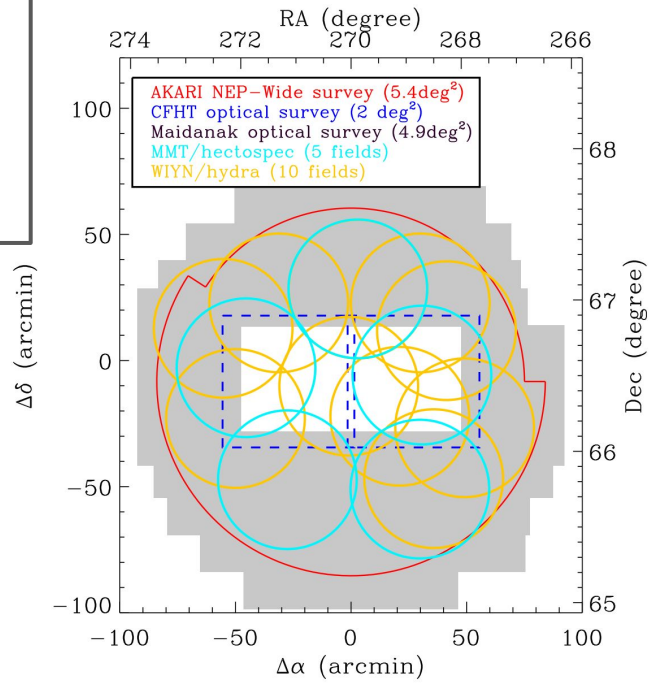
Made with Napkin

AIM: Creating science ready catalogue

Astronomy & Astrophysics manuscript no. 425-merger-catalogue-NEP
February 23, 2022
©ESO 2022

North Ecliptic Pole merging galaxy catalogue★

W. J. Pearson[1], L. E. Suelves[1], S. C.-C. Ho[2], N. Oi[3], S. Brough[4], B. W. Holwerda[5], A. M. Hopkins[6], T.-C. Huang[7,]
H. S. Hwang[9], L. S. Kelvin[10], S. J. Kim[2], Á. R. López-Sánchez[6,11,12], K. Małek[1,13], C. Pearson[14,15,16],
A. Poliszczuk[1], A. Pollo[1], V. Rodriguez-Gomez[17], H. Shim[18], Y. Toba[19,20,21], and L. Wang[22,23]



Merger Catalogue by Pearson et al. 2022 covers **redshift < 0.3**

NEP field: **5.4 deg²** , multi-wavelength coverage





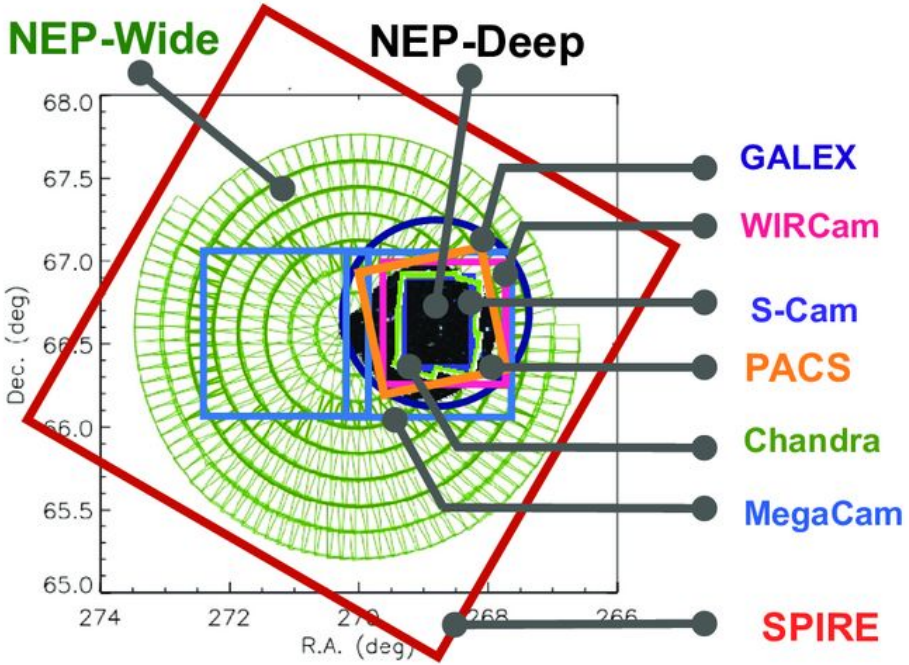

AIM: Creating science ready catalogue

NEP field : 5.4 deg², multi-wavelength coverage

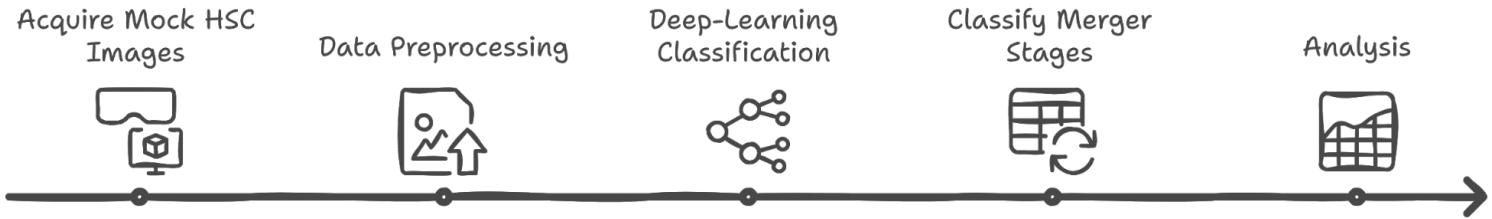
Xray , UV, Optical, IR and Radio

👉 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

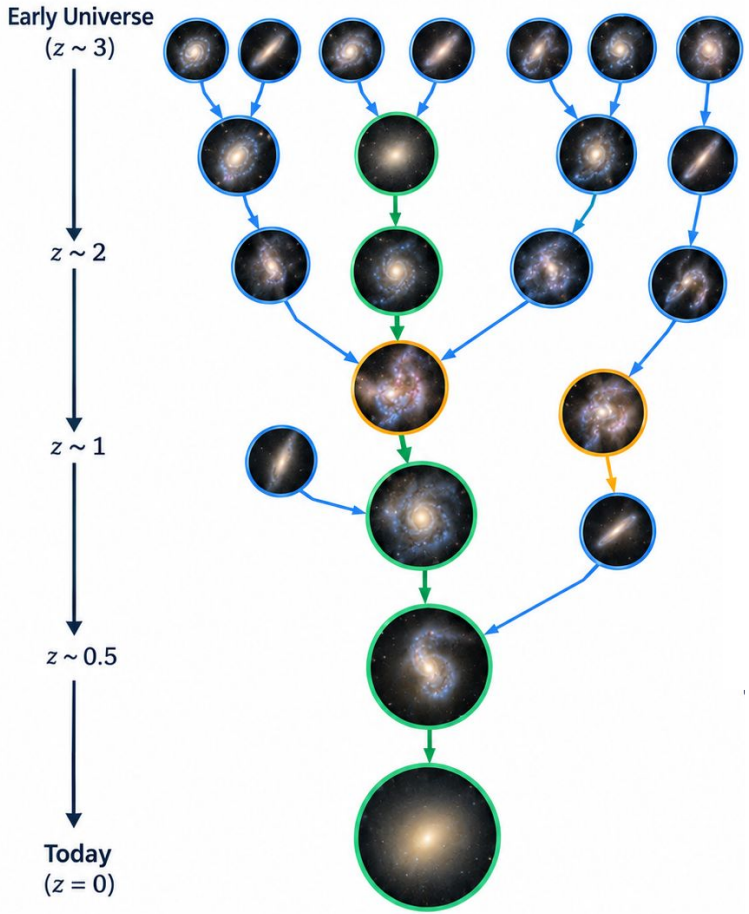
A&A, 687, A24 (2024)
https://doi.org/10.1051/0004-6361/202348239
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Astronomy & Astrophysics

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]

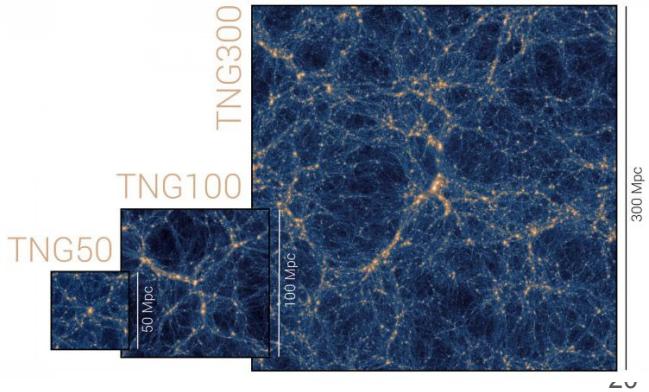
Merger Tree



Main progenitor
(the galaxy we follow)

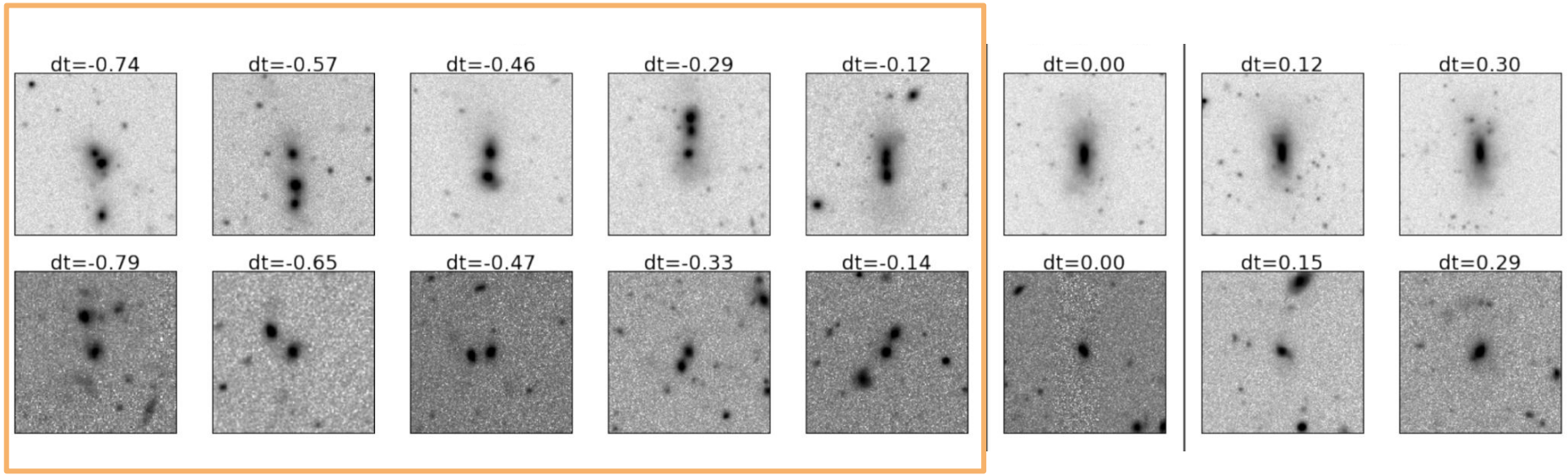
Other progenitor
(merging in)

Merger event
(two galaxies combine)



Merger definition

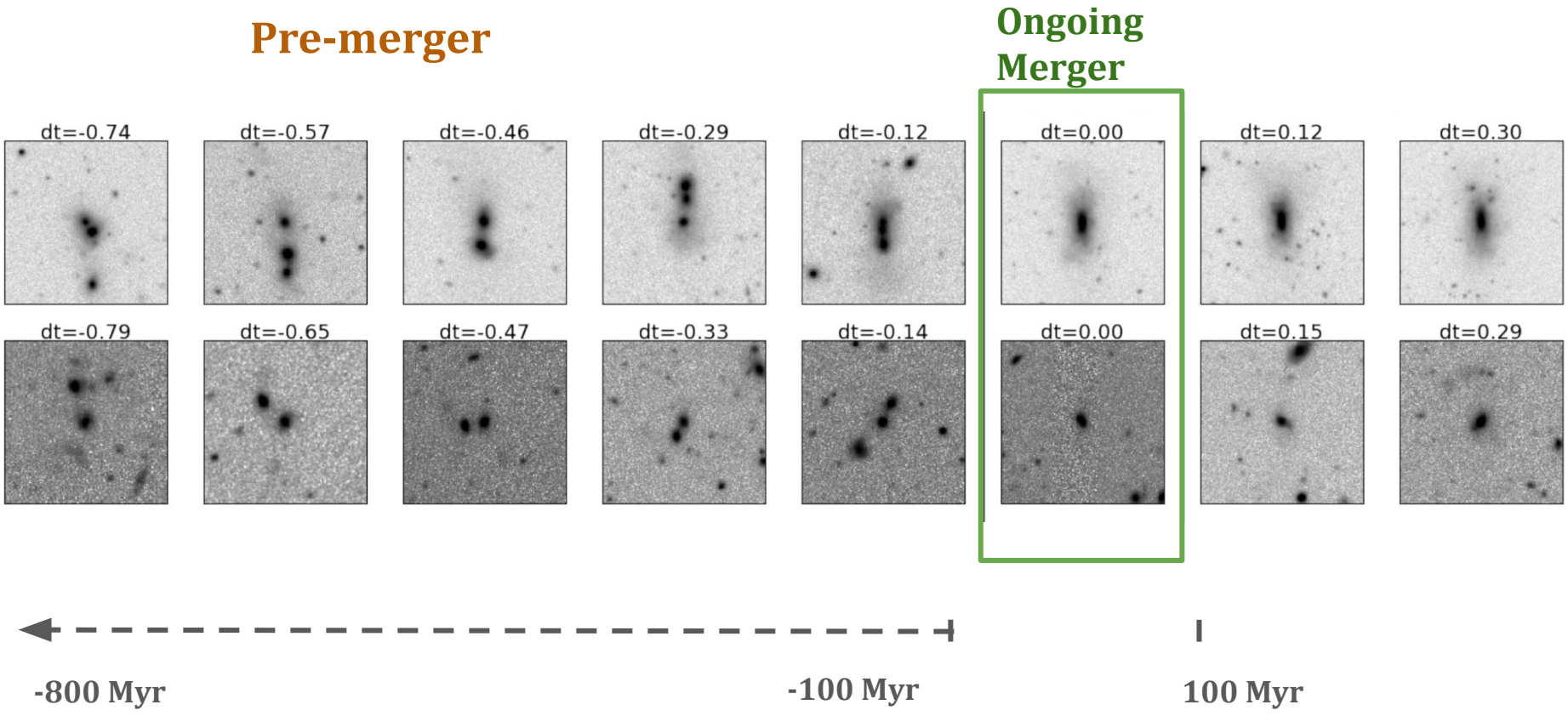
Pre-merger



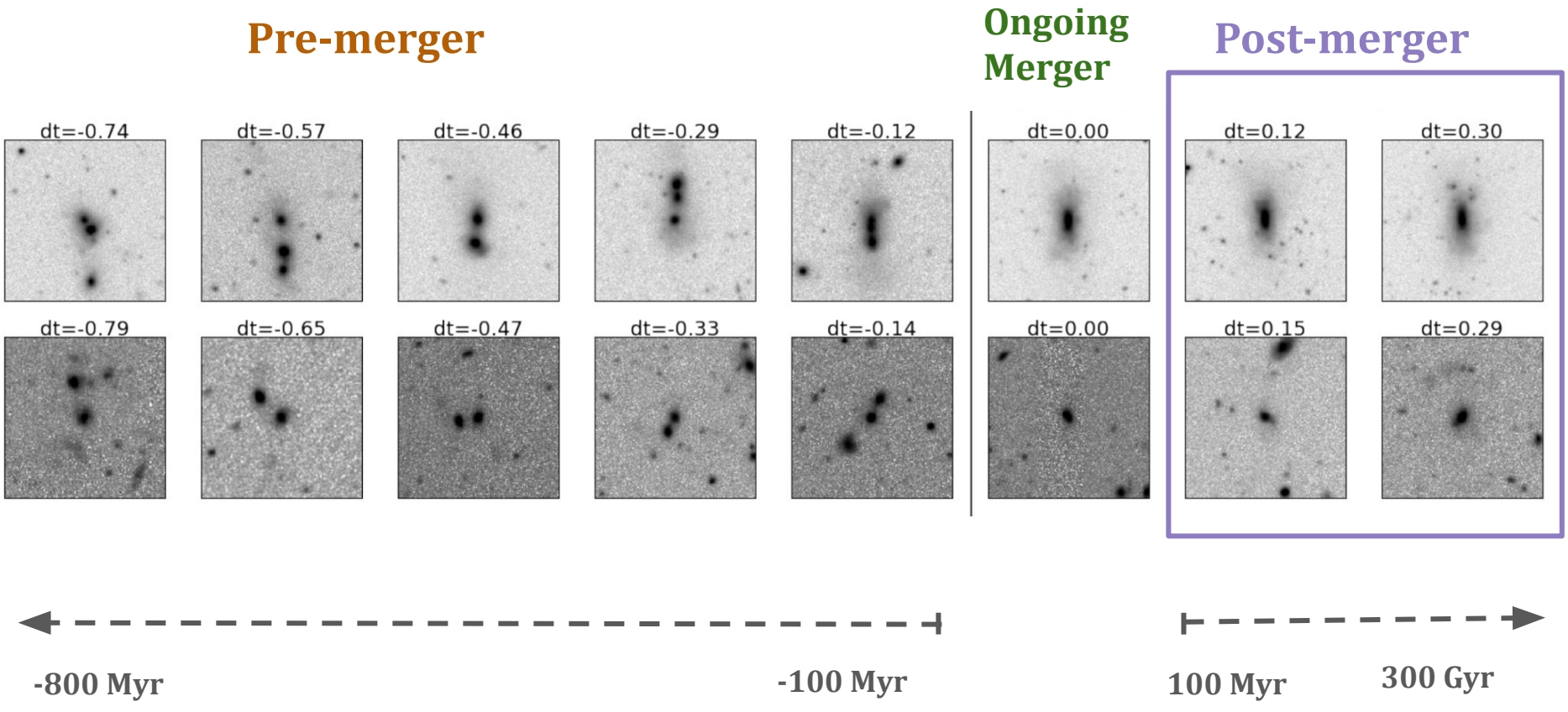
-800 Myr

-100 Myr

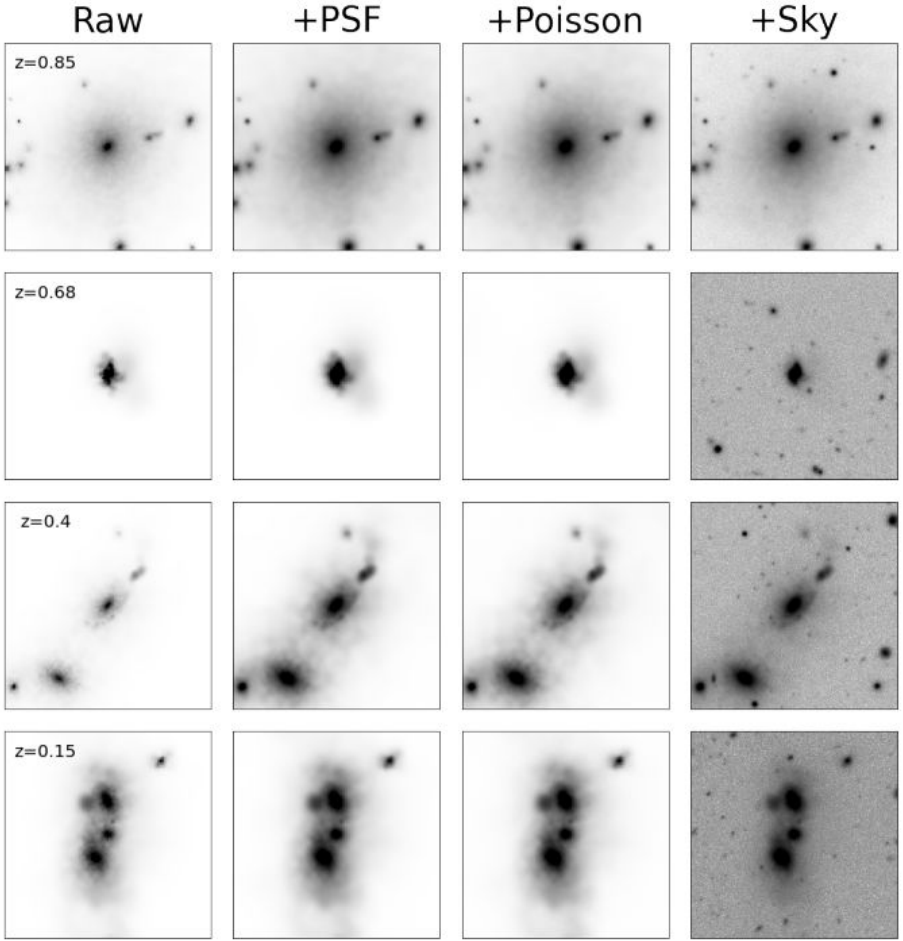
Merger definition



Merger definition



Mock HSC images

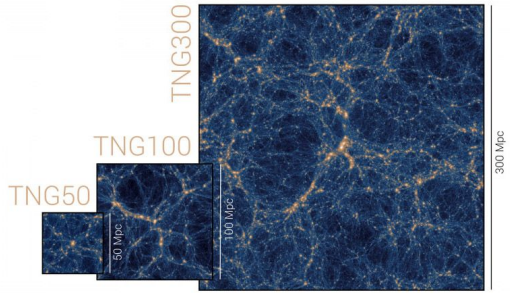


Simulations:

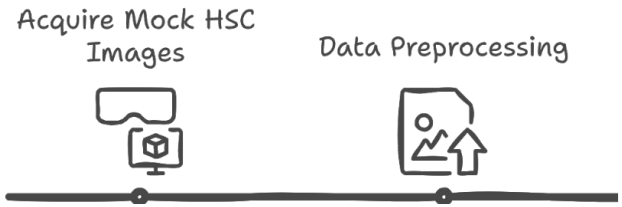
TNG300 → chosen for its large number of galaxies

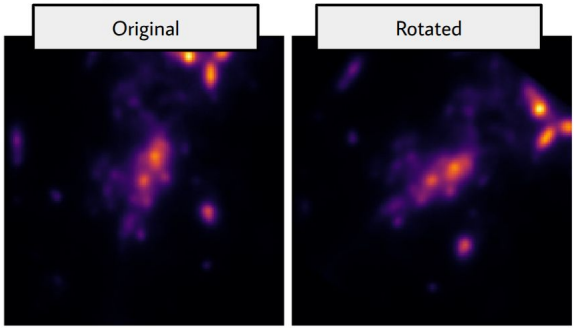
TNG100 → included to probe lower-mass galaxies

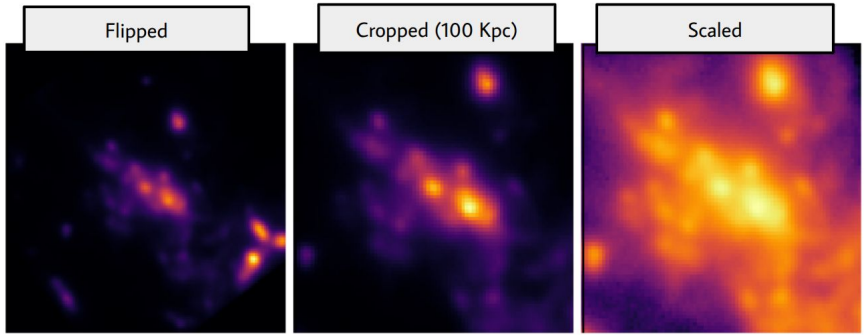
Redshift range: 0.1 - 1.0



Data preprocessing

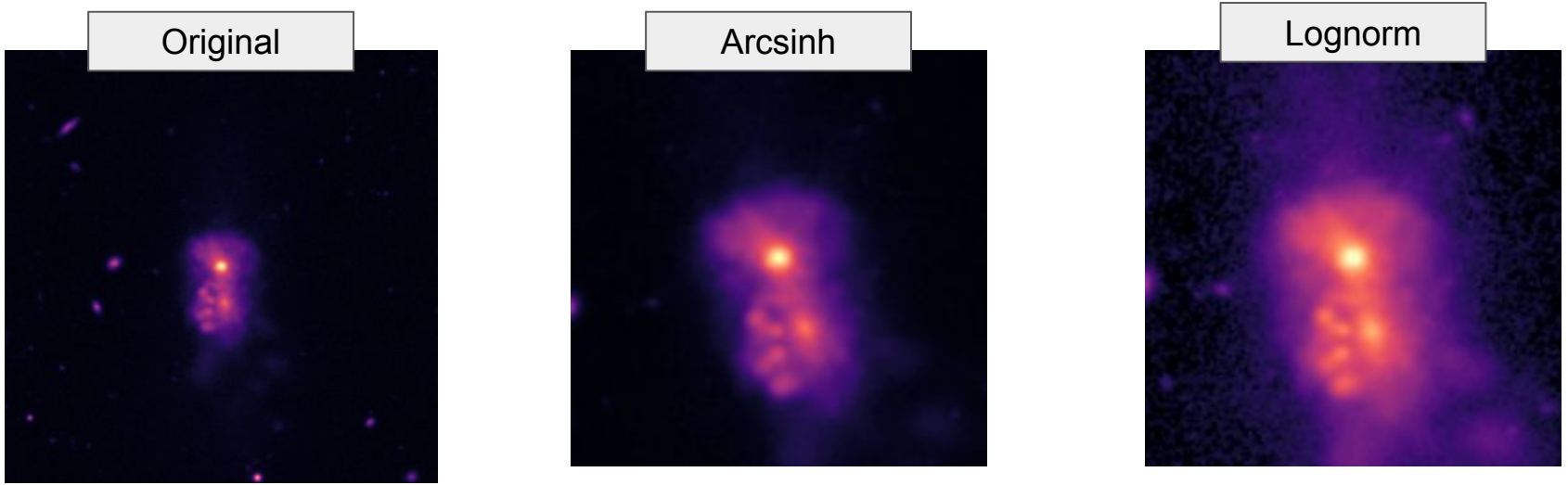






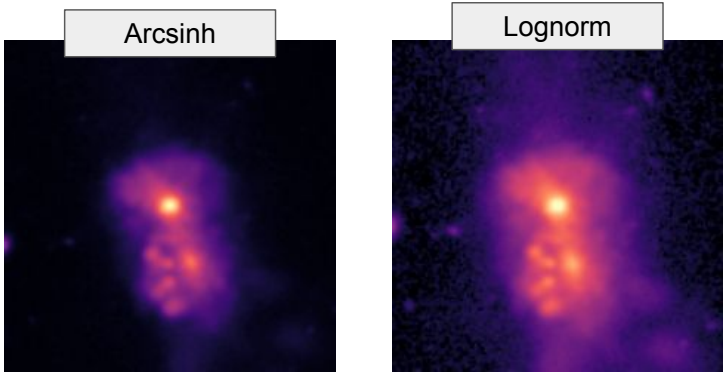
Data preprocessing





Deep learning merger classification





Base deep learning networks:

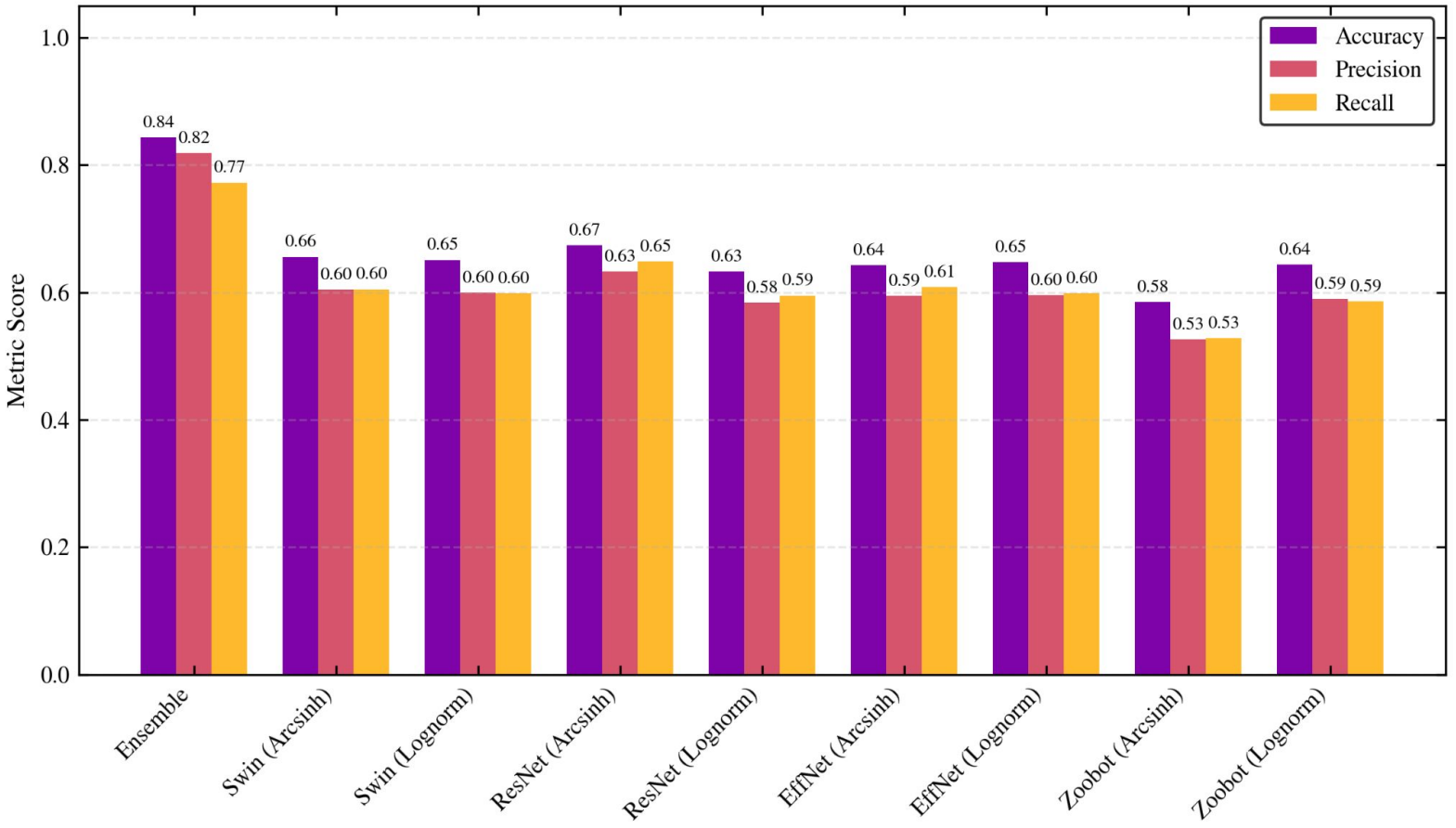
- Zoobot ConvNeXt
- EfficientNet-B3
- ResNet-18
- Swin Transformer (SwinT)

Ensemble :

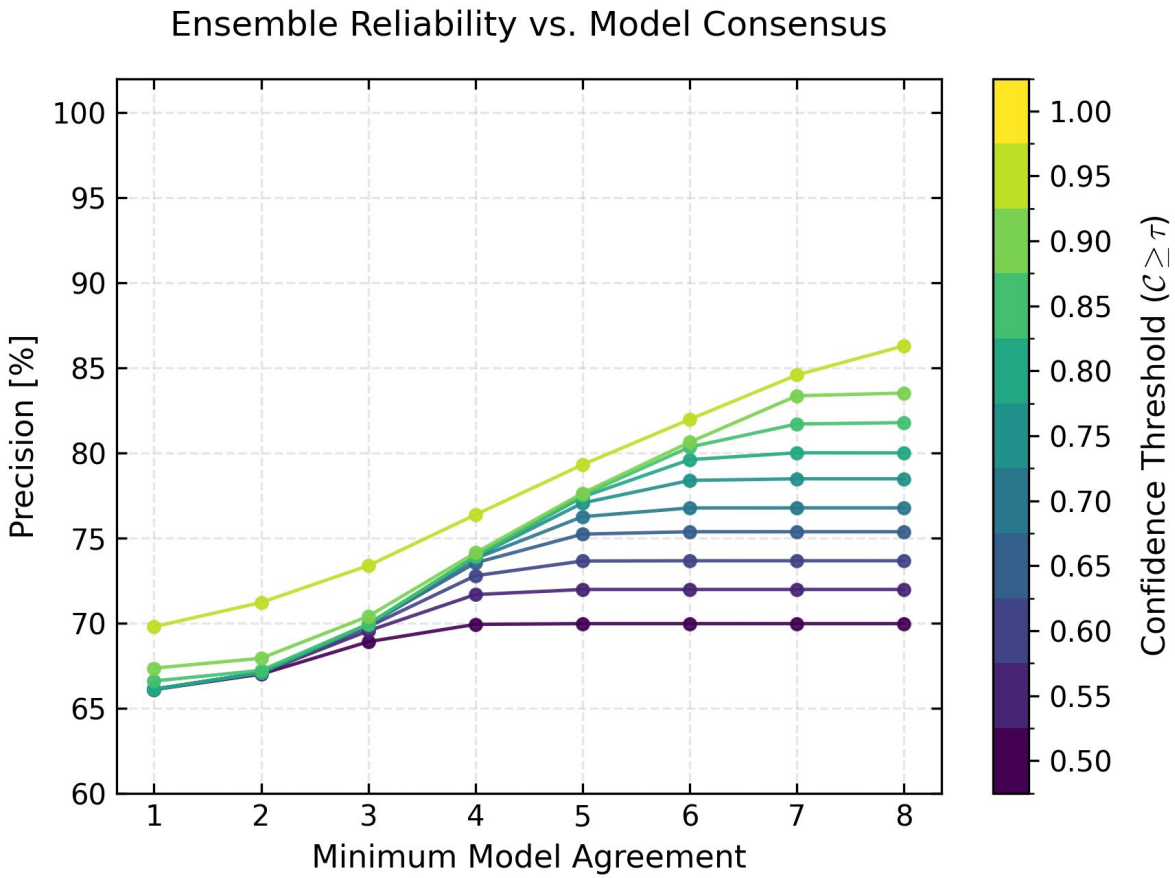
Combination of 8 independently trained models

Final prediction obtained via ensemble voting

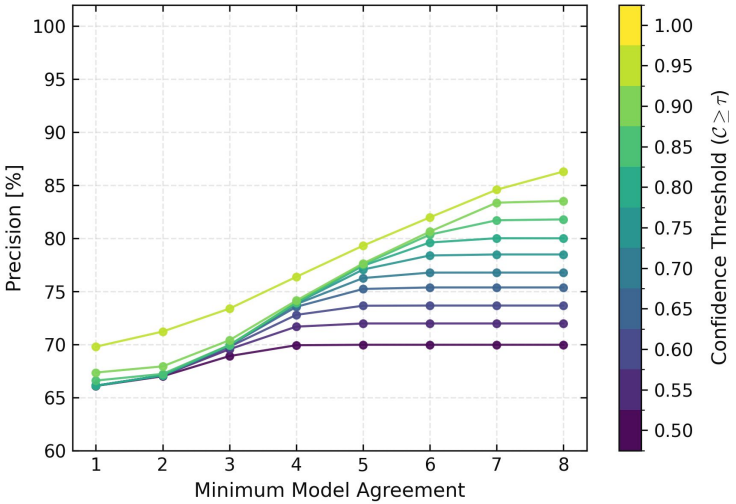
Classifier performance

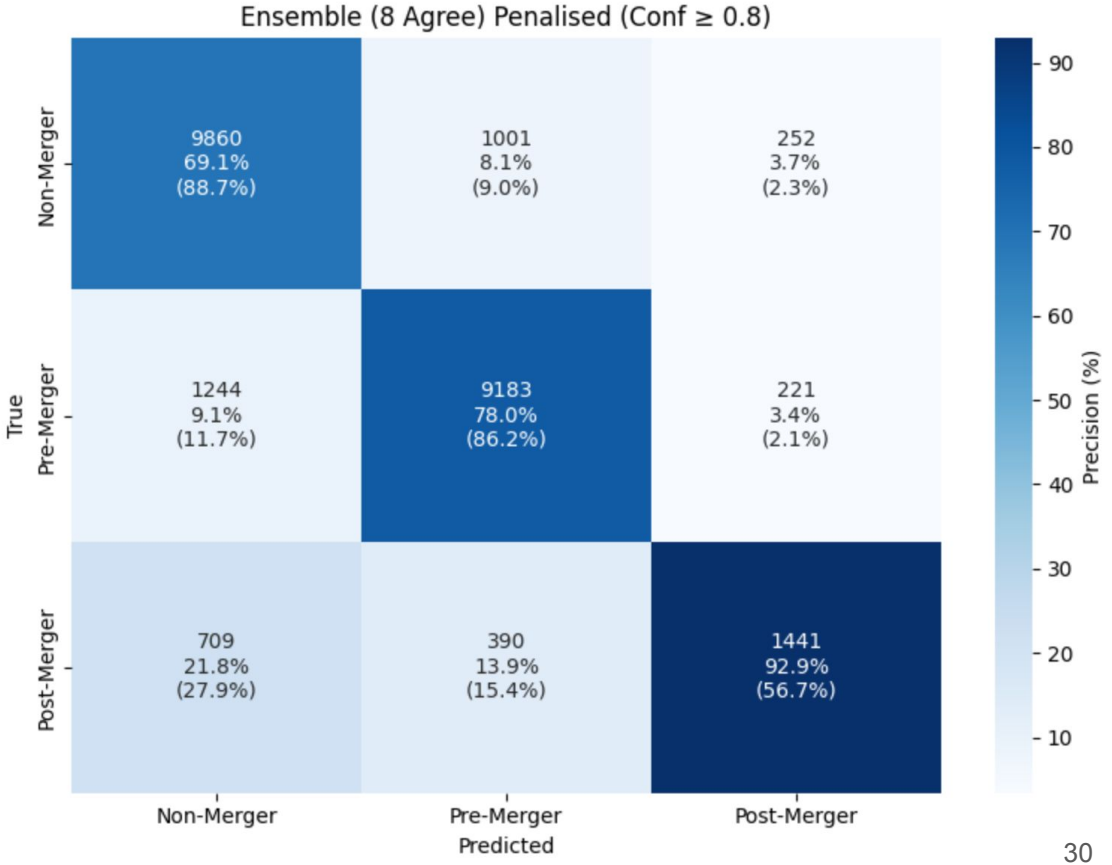


Ensemble performance

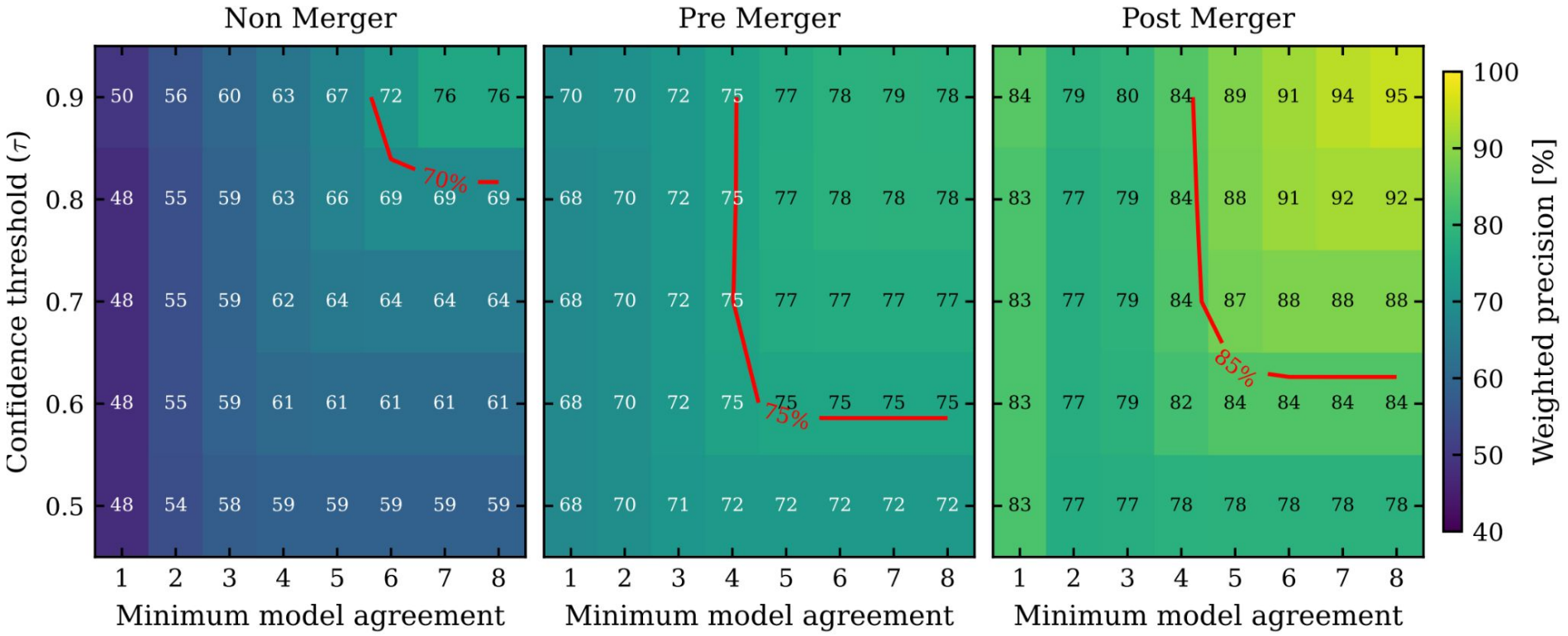


Ensemble performance

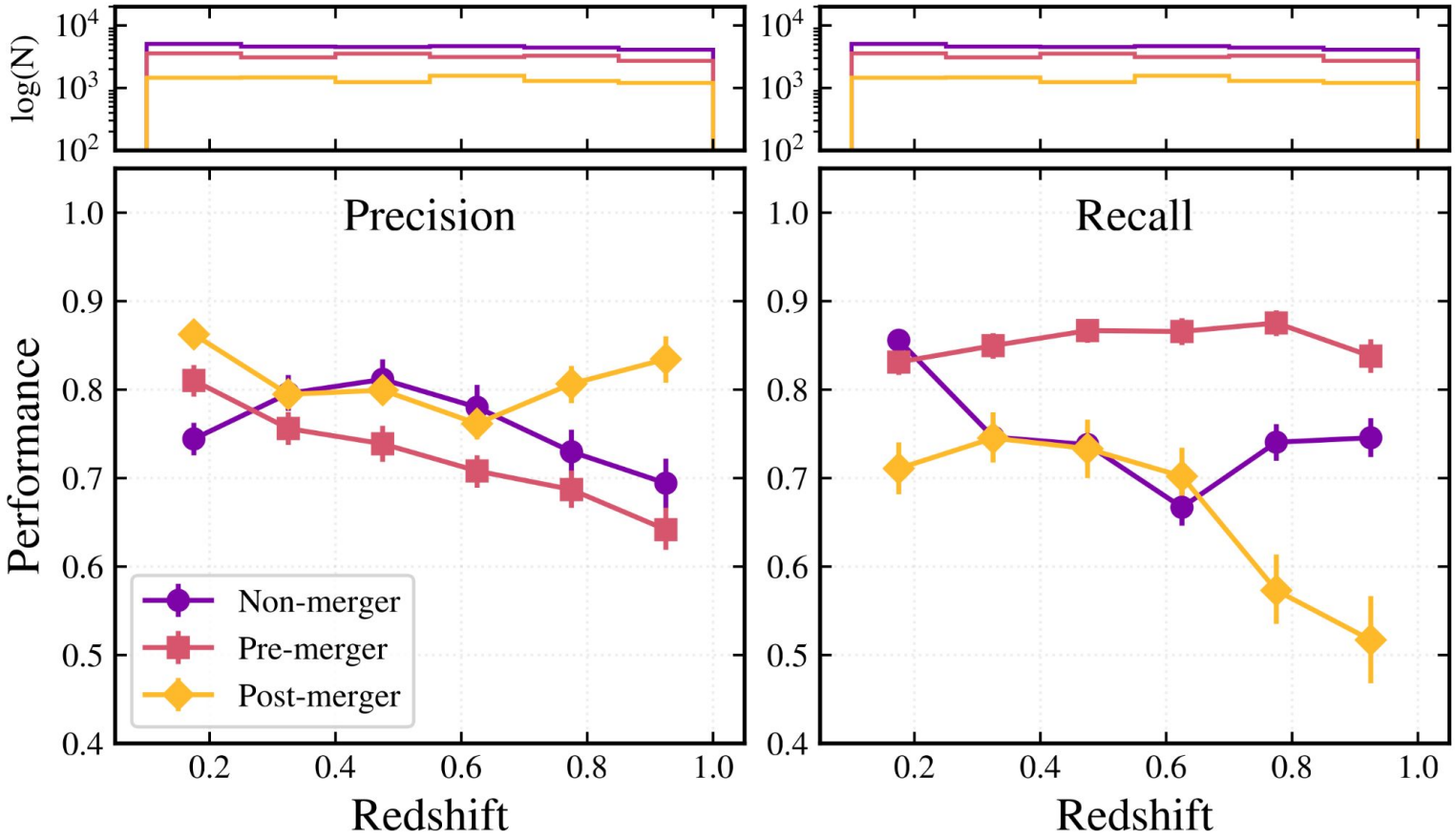




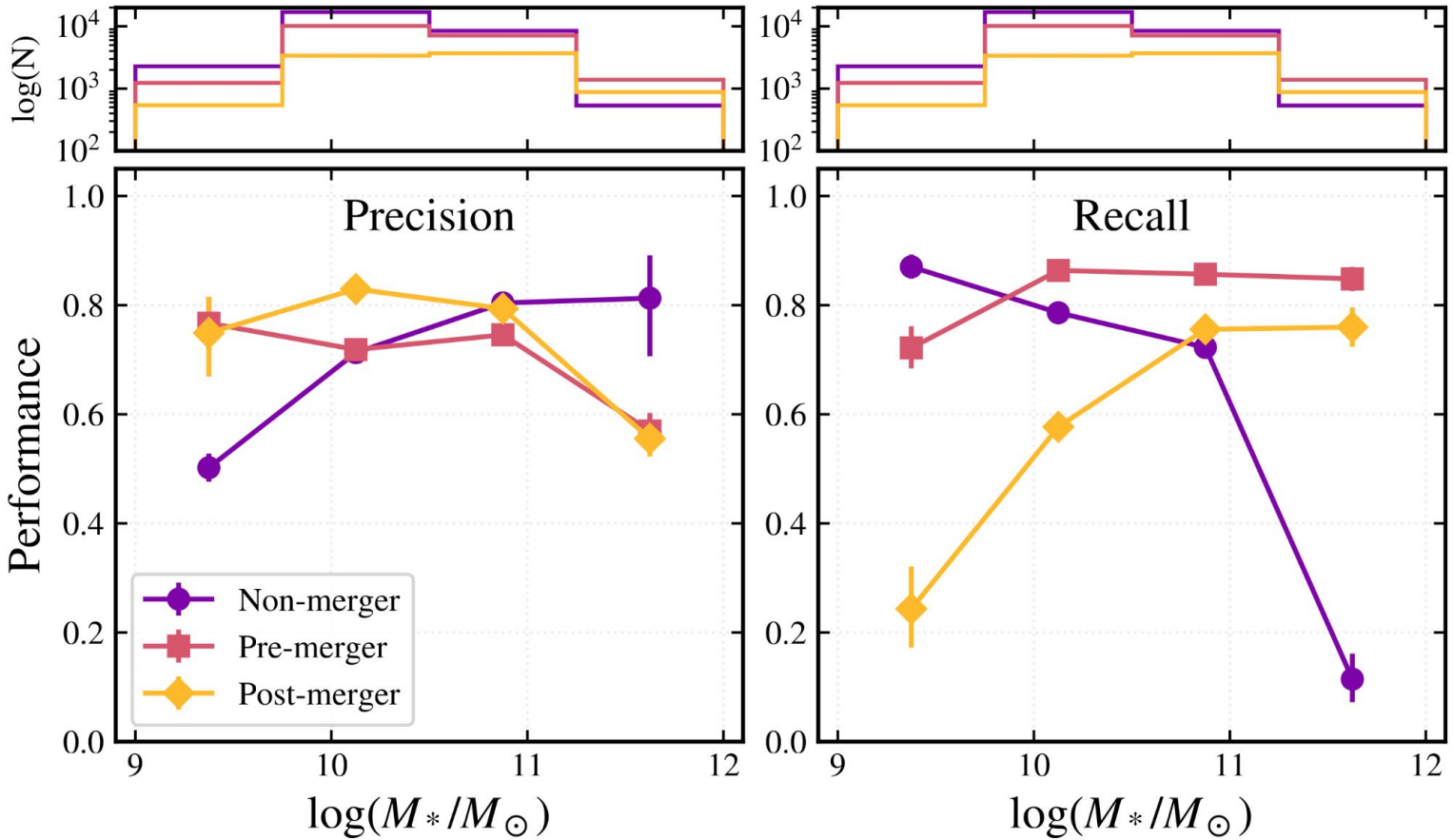
Ensemble performance



Ensemble performance vs redshift

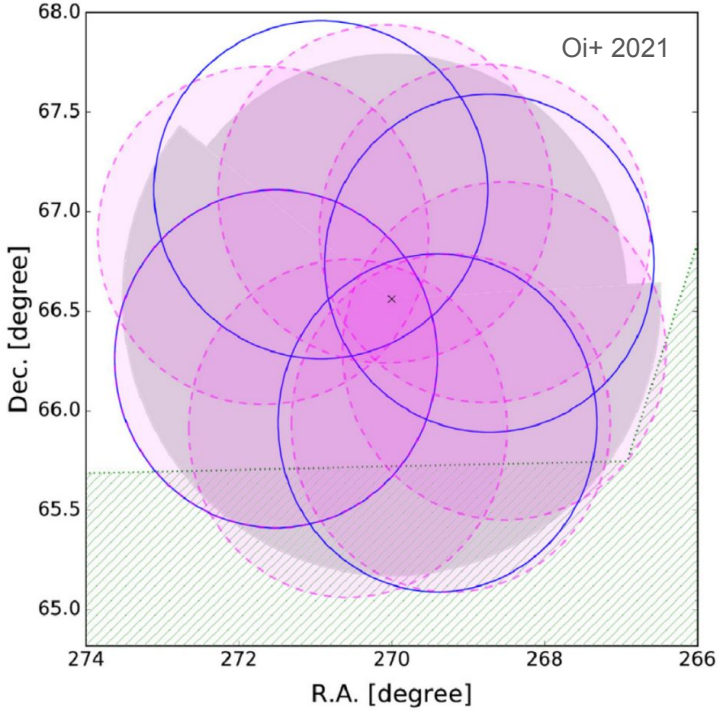


Ensemble performance vs mass

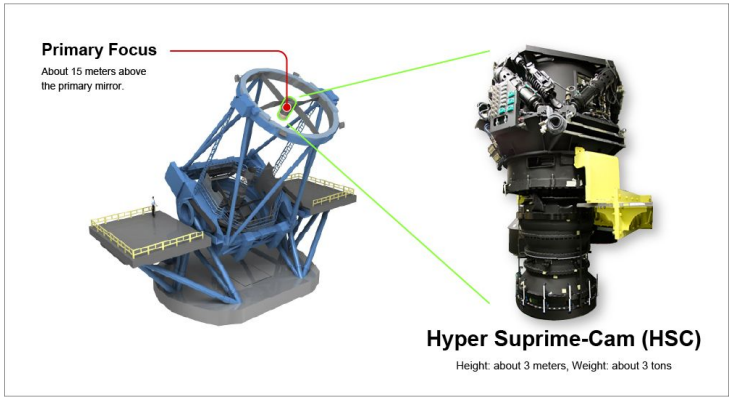


Moving from simulation to observations!

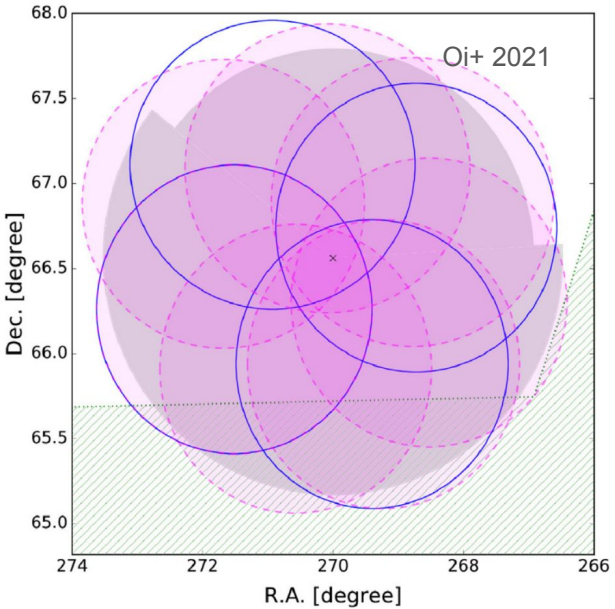
HSC observations of the AKARI-NEP field



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.



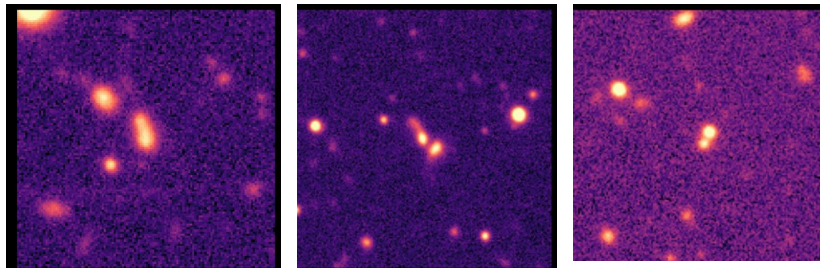
Merger predictions



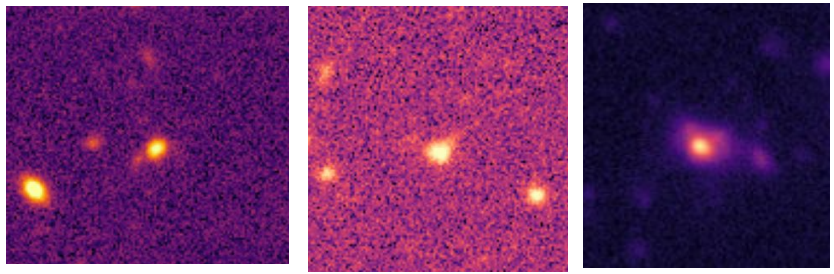
Prediction based on ensemble of networks

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

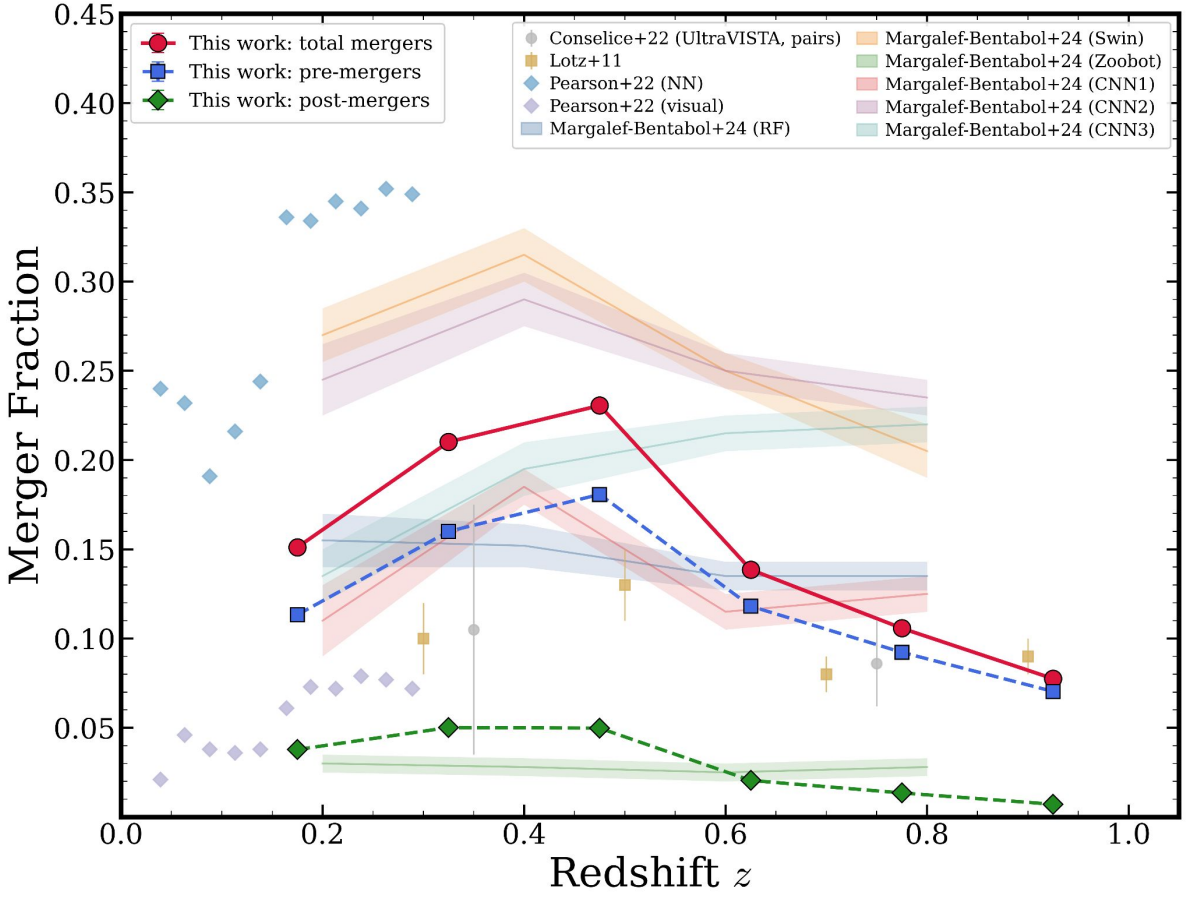
Pre-mergers



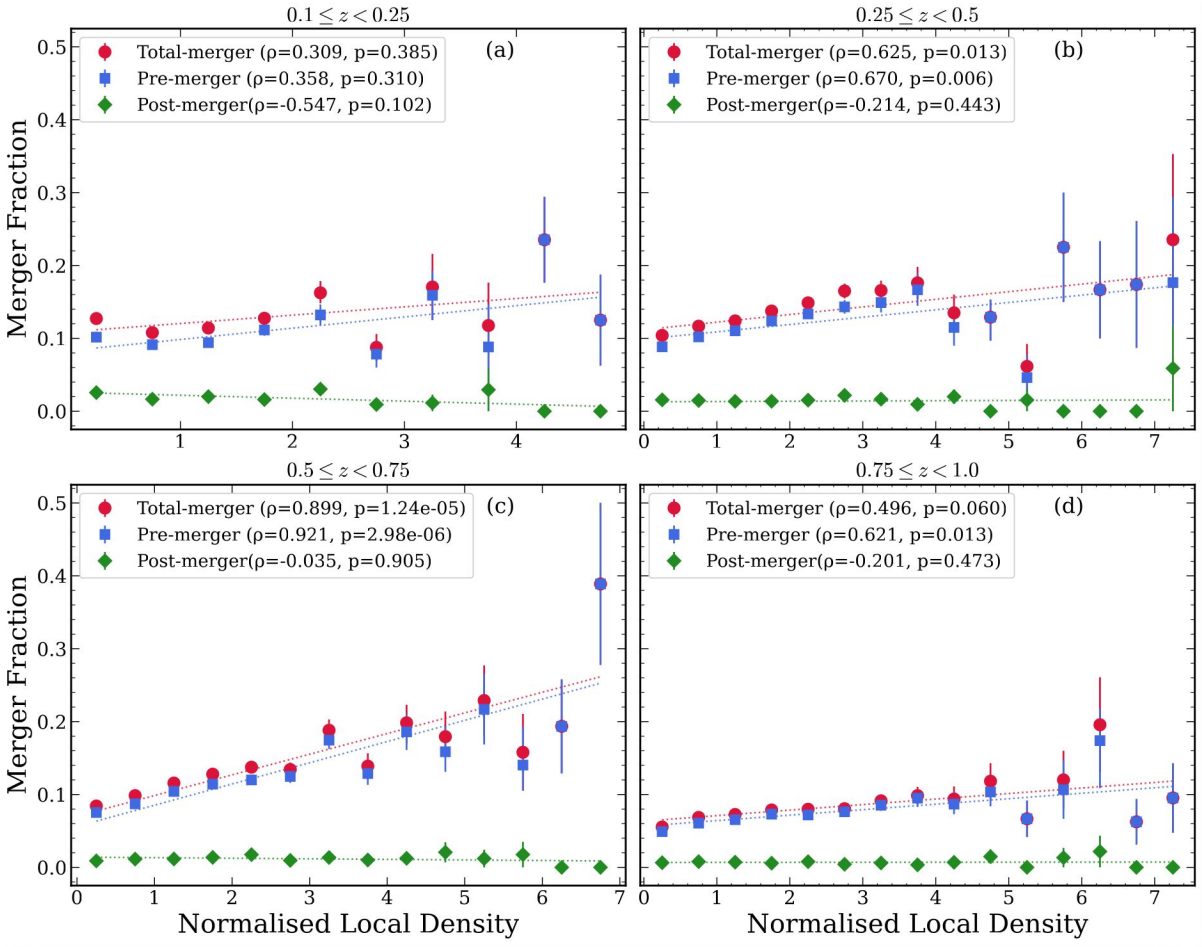
Post-mergers



Merger fraction versus redshift

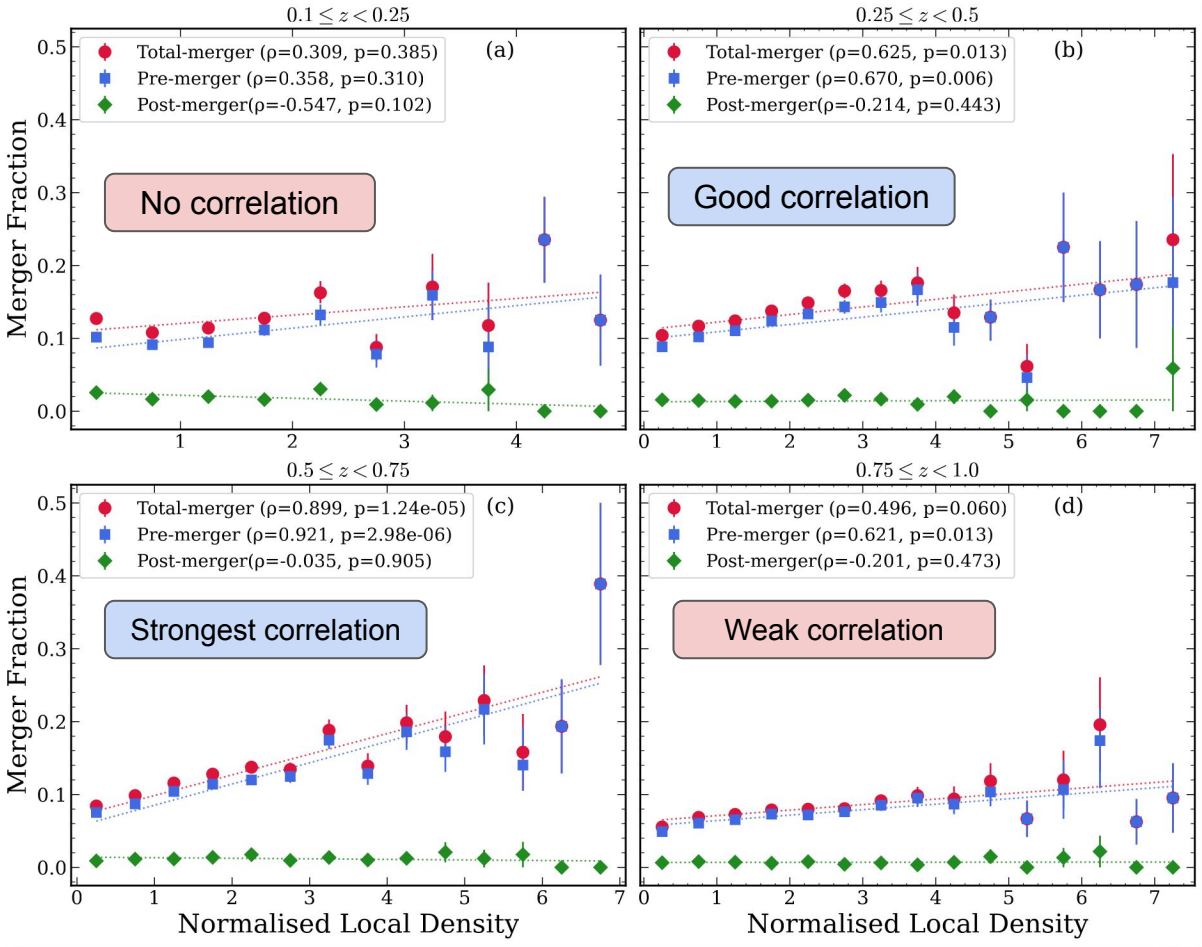


Merger fraction versus normalised local density



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

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 !!

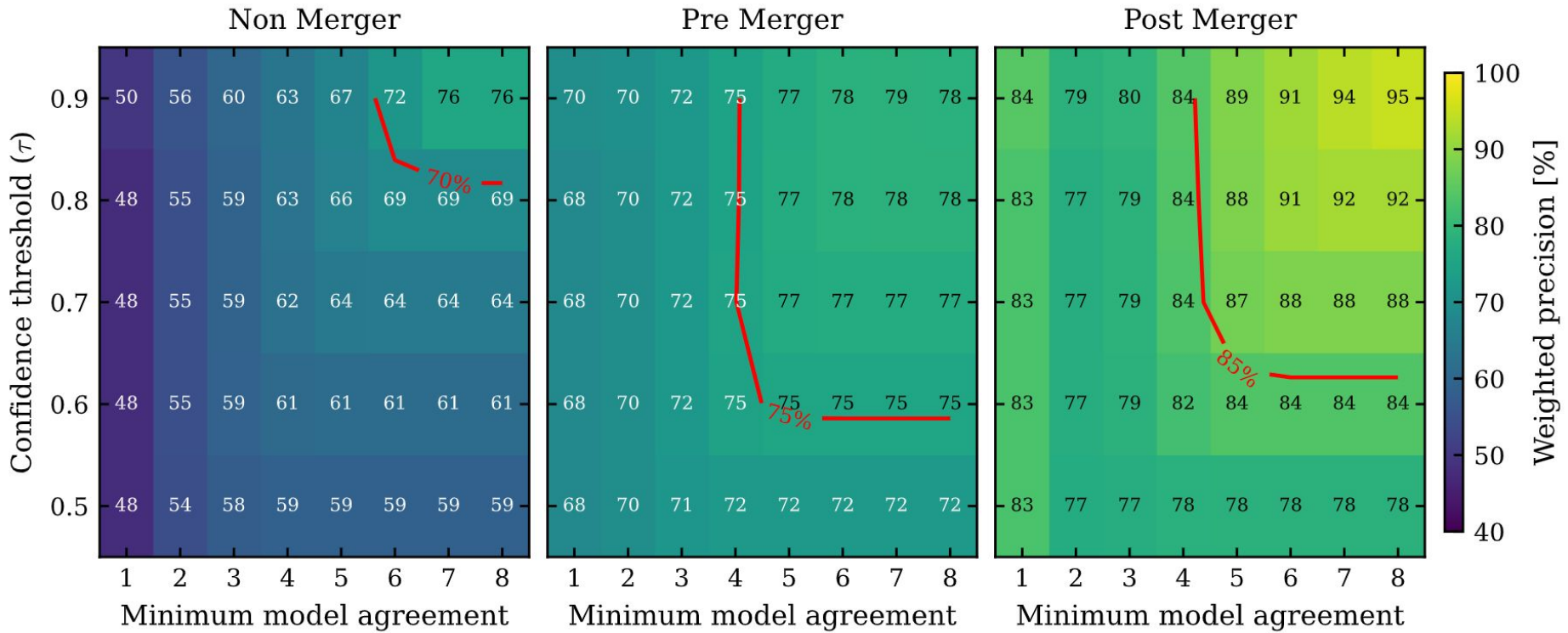
=>shorter-lived observable signatures after coalescence.

Summary

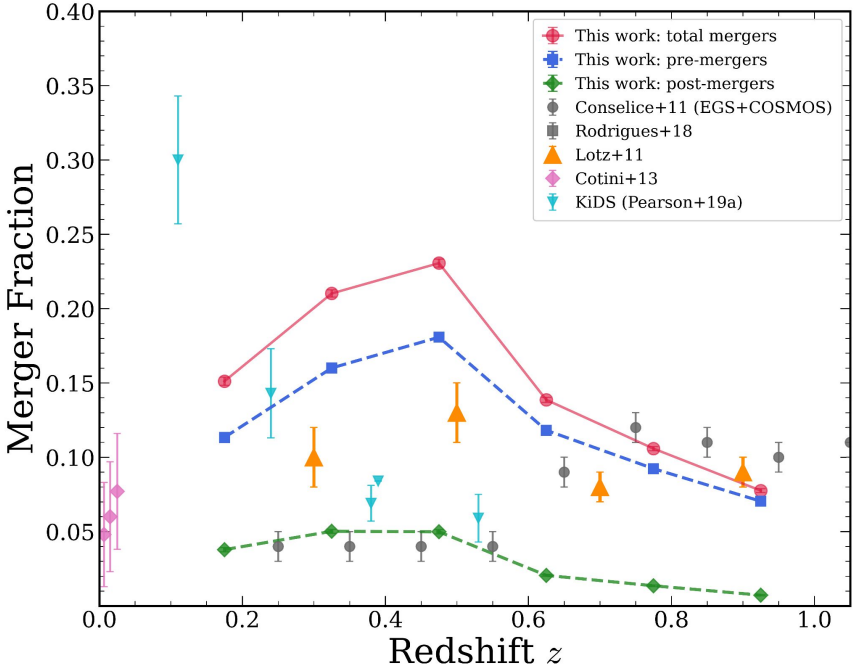
- ★ **Ensemble of 8 deep-learning networks** achieved the best merger-stage classification performance.
- ★ Classification performance is **strongly mass-dependent,** with significant variations in recall across stellar mass ranges.
- ★ **Merger fraction peaks at intermediate redshift (z ≈ 0.4–0.5) and 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.

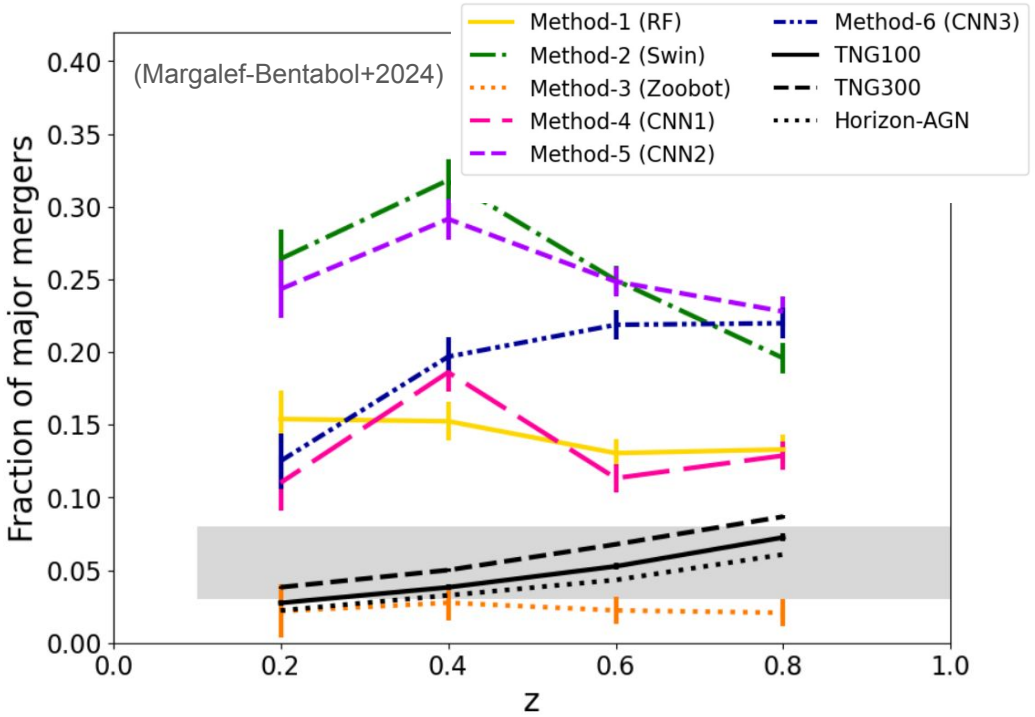
Thank You :)

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

Merger fraction versus redshift



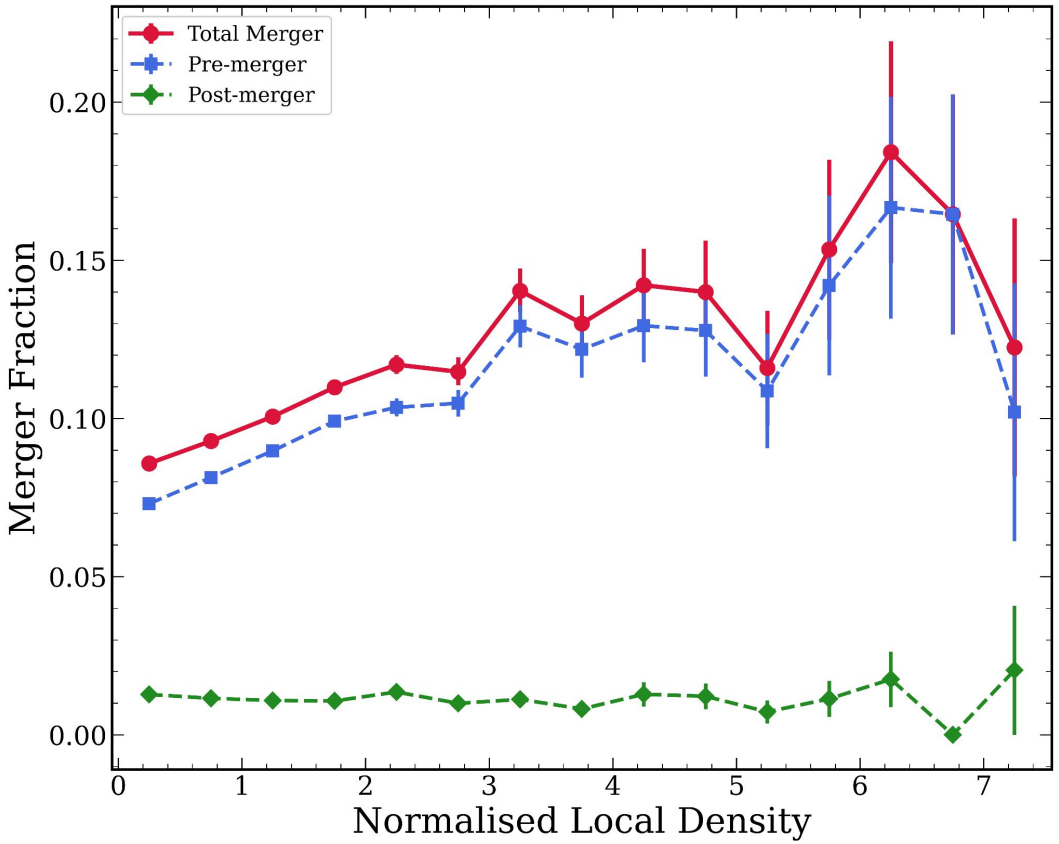


observational limit! As we go to higher redshifts, the images become fainter, making it harder for a DL network to 'see' the merger signatures.

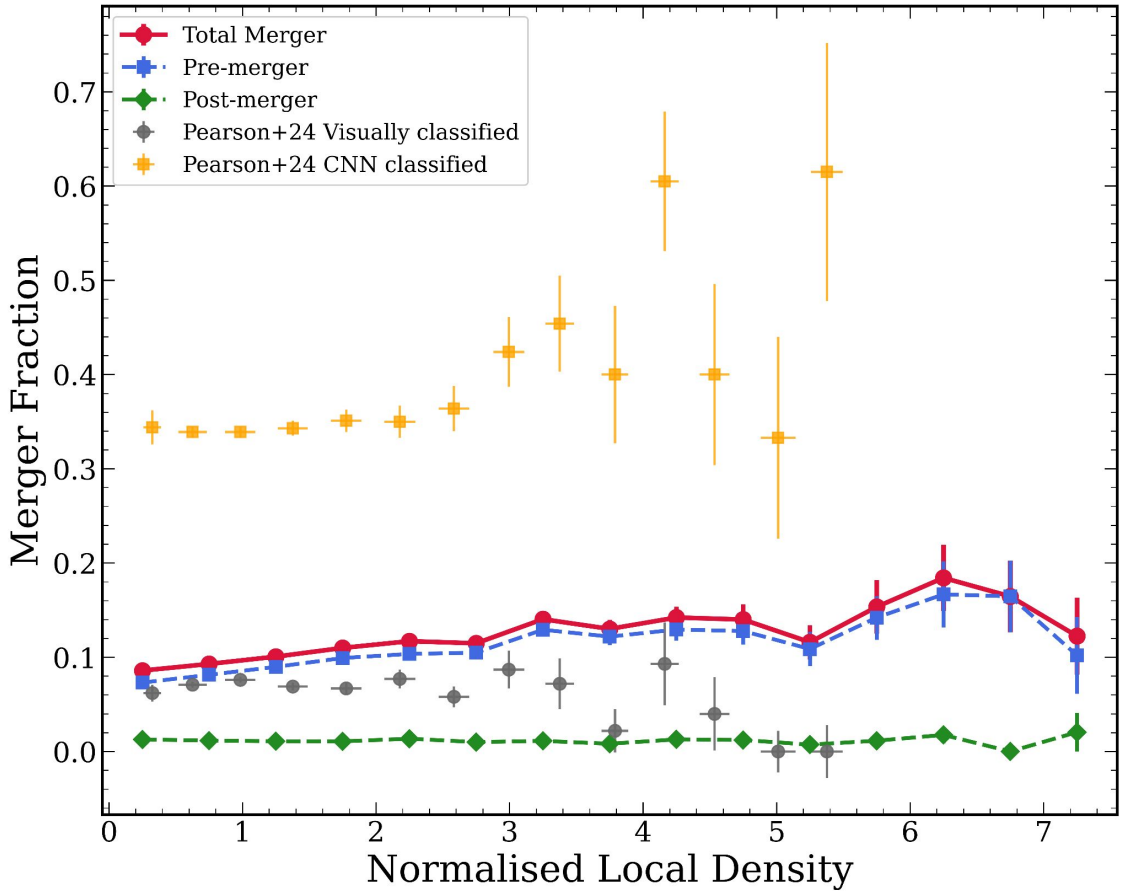
Merger fraction versus normalised local density

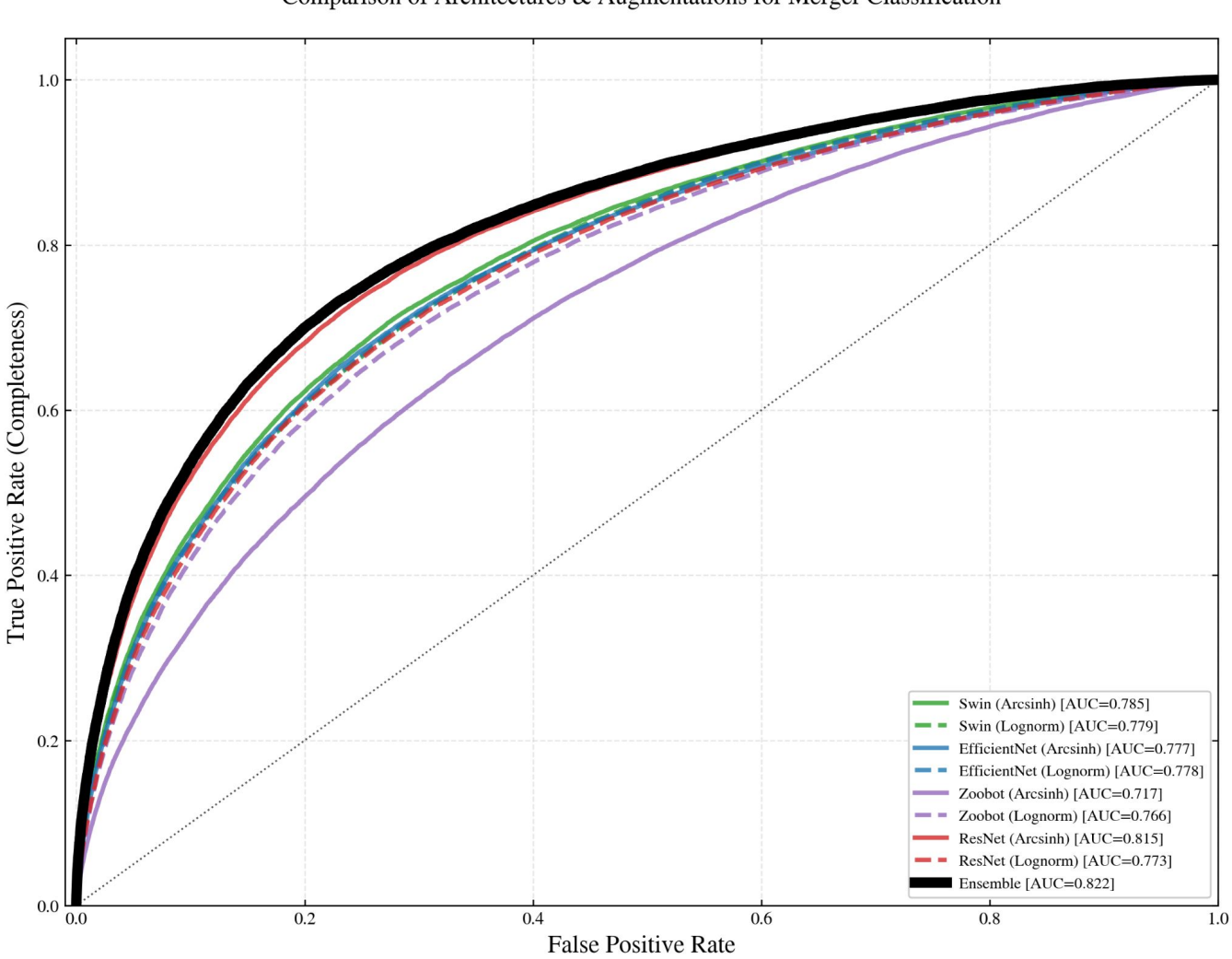
Local densities : 10th nearest neighbour in 2-dimensions using only galaxies within a redshift bin of width 0.065 × (1 + *z*) (Santos+ 21)

Galaxies in denser environments have a higher probability of interacting.

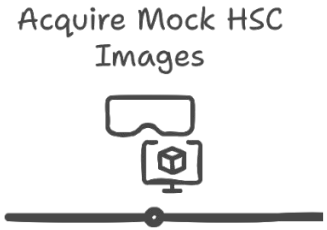


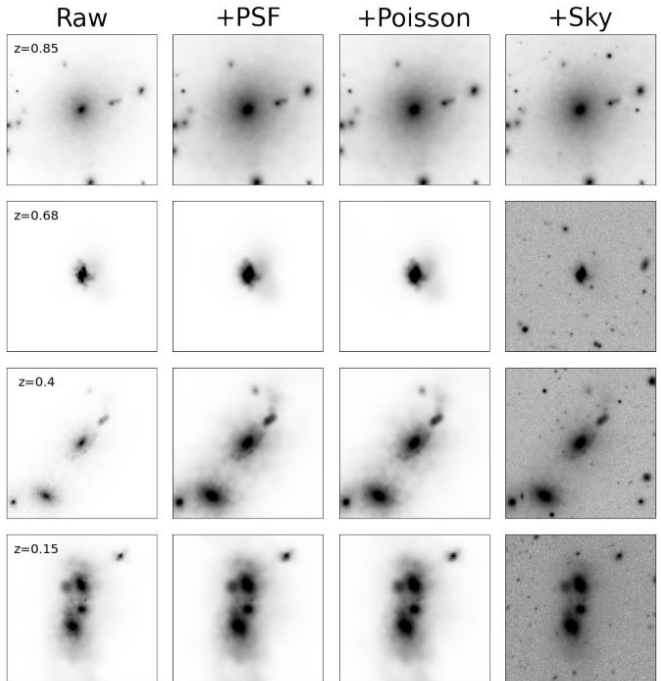
Merger fraction versus local density




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



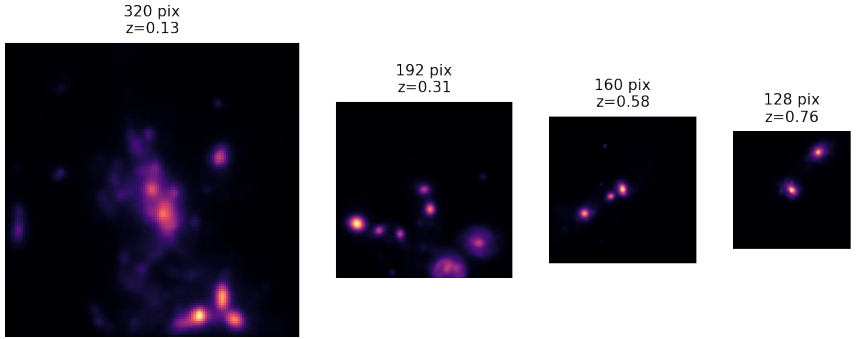


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Astronomy & Astrophysics

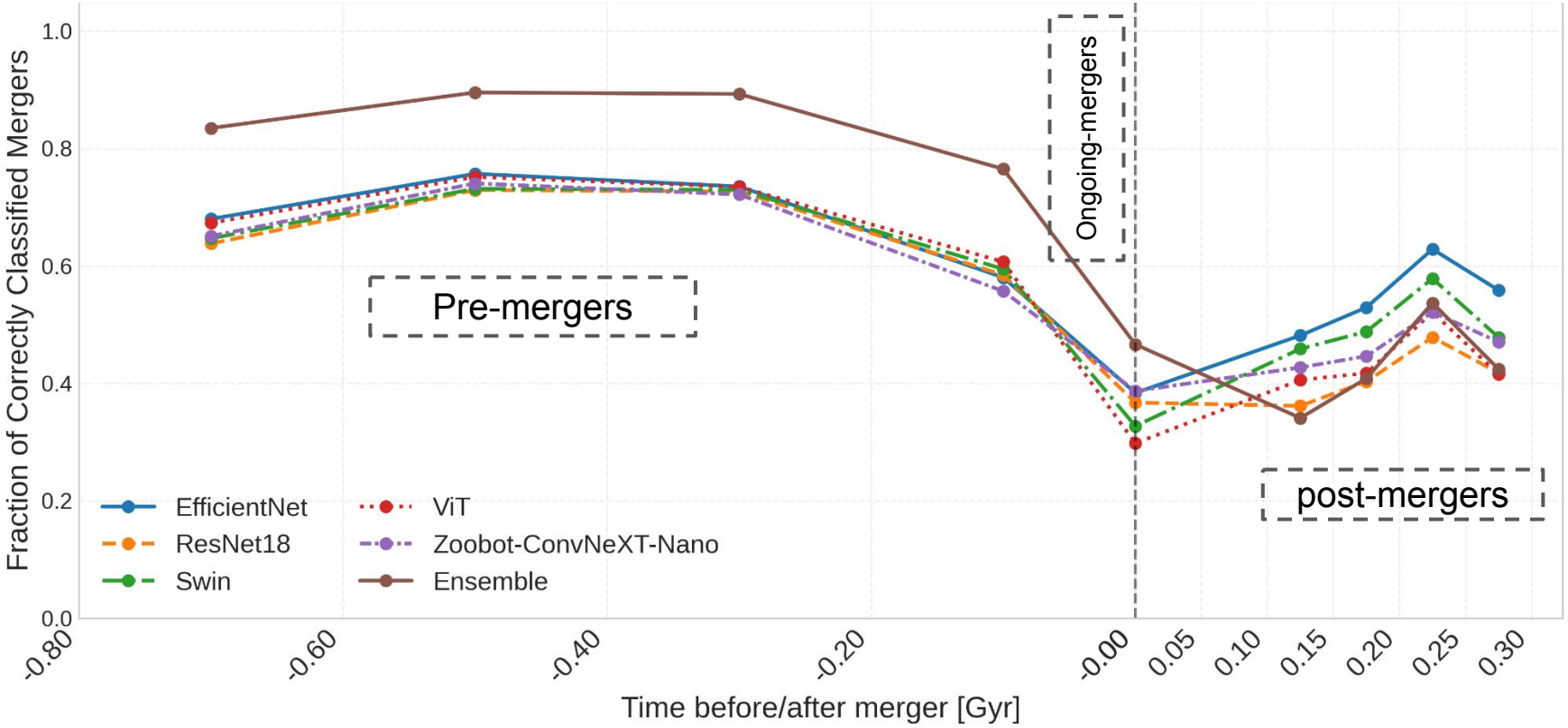
Galaxy merger challenge: A comparison study between machine learning-based detection methods

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]

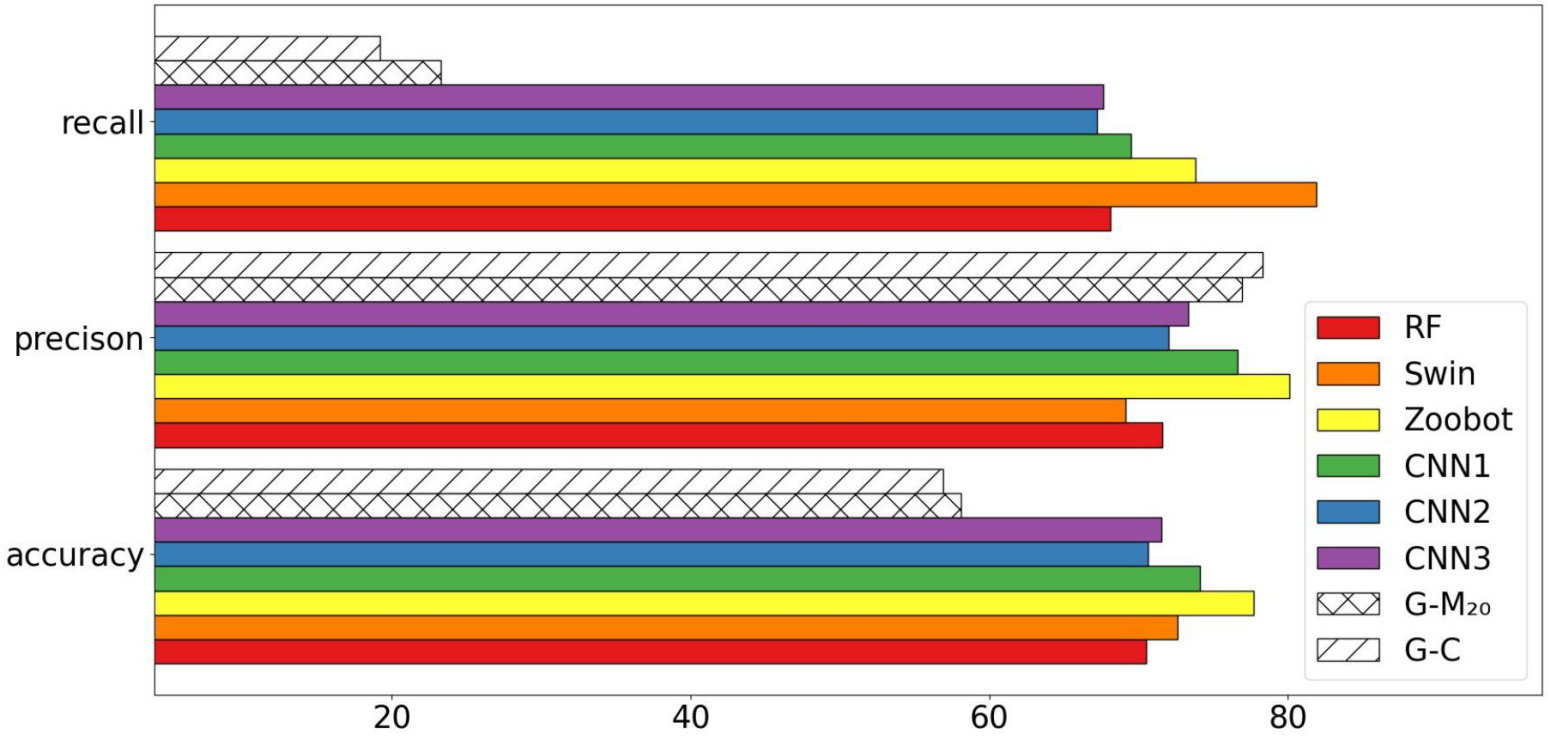


z= 0.10–0.31 0.31–0.52 0.52–0.76 0.76–1.00

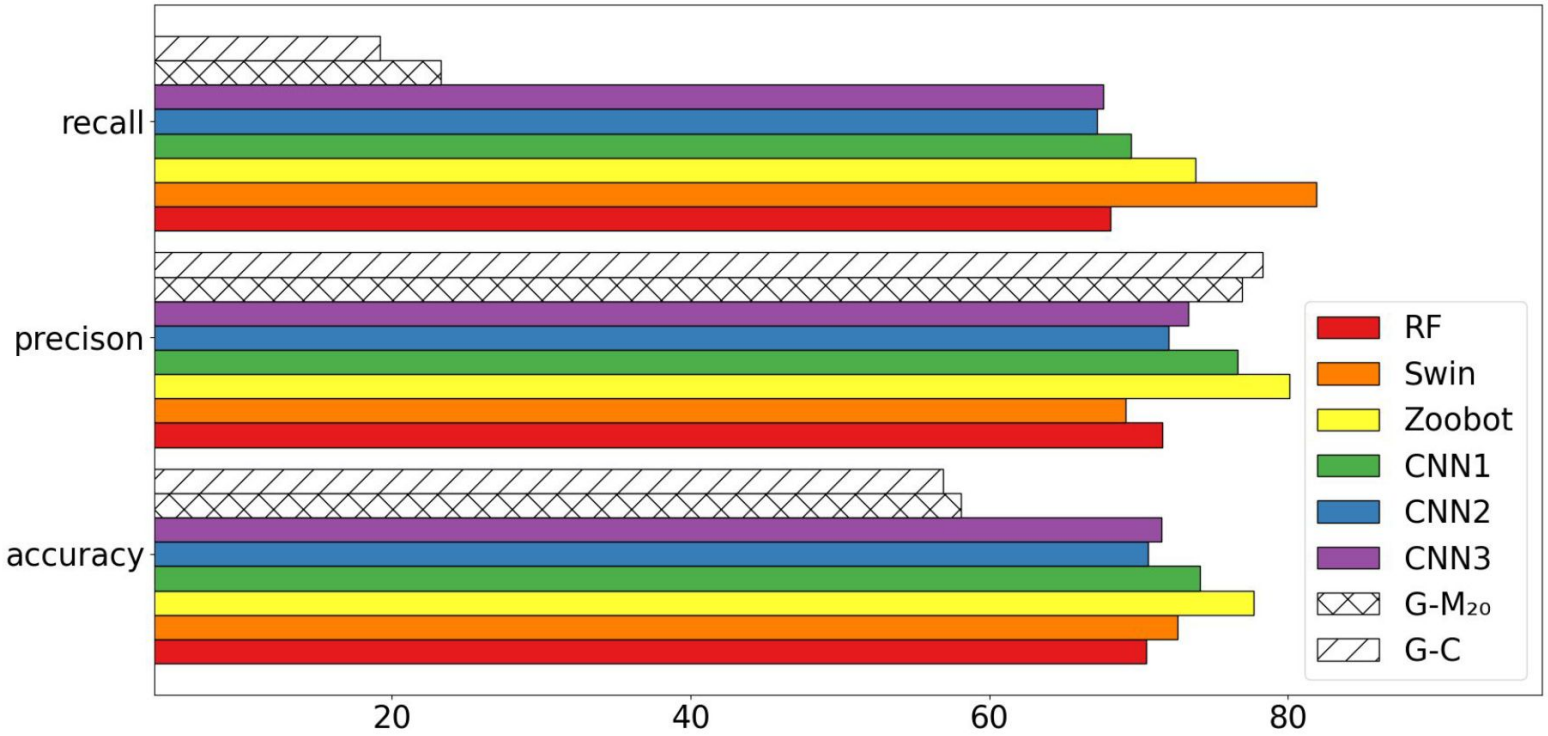
Fraction of correctly classified Mergers vs Merger times



Morphological statistics

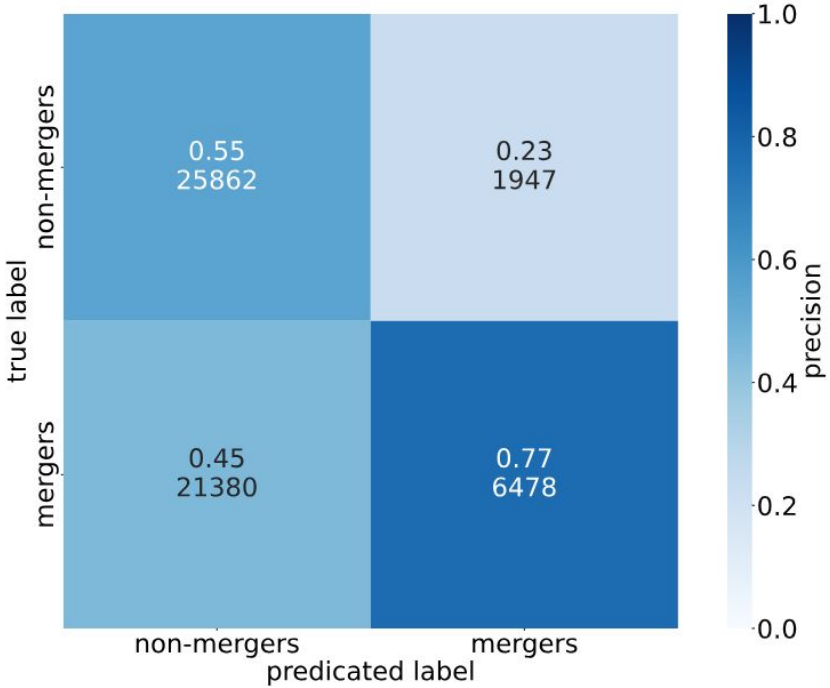


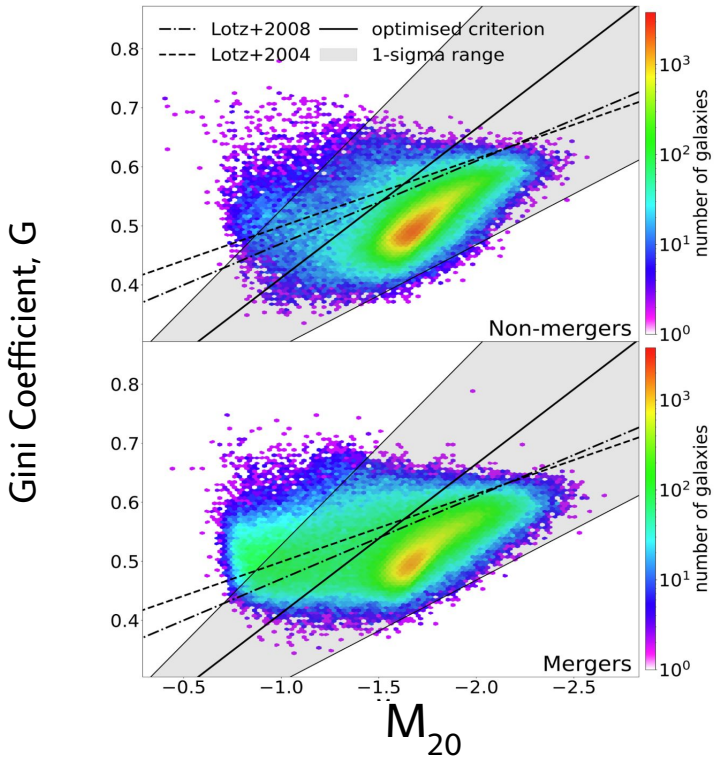
Morphological statistics



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

Morphological statistics





Cotter et al. (in prep)

G > (-0.253±0.081) M_{20} + (0.159±0.035)