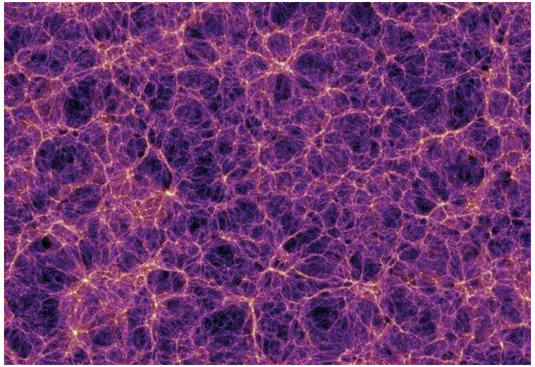
Meeting new challenges in low surface-brightness astronomy with the next generation of cosmological simulations

Garreth Martin
with
LSST Galaxies LSB Working Group
&
The Horizon Collaboration

Steward Observatory/NOIRLAB Joint Colloquium, Tucson, *2023-04-27*

The hierarchical assembly of galaxies is fundamentally linked to conditions in the primordial Universe, which inform the growth of the cosmic large scale structure in which galaxies grow and evolve.



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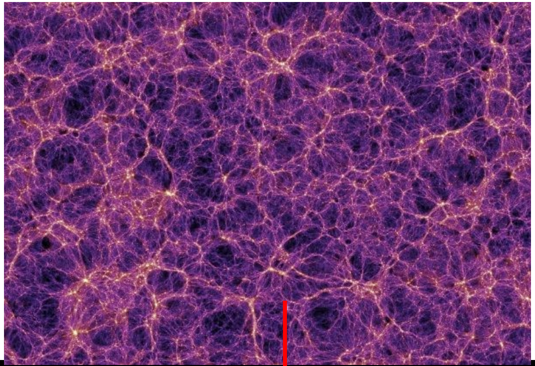
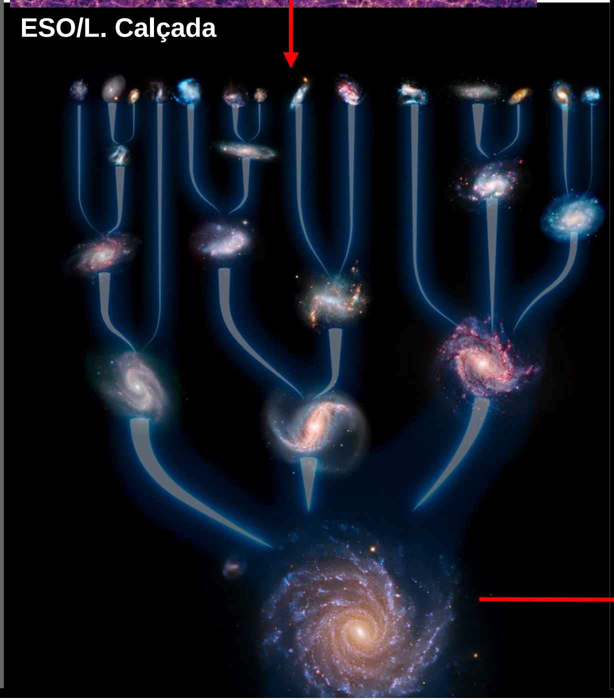
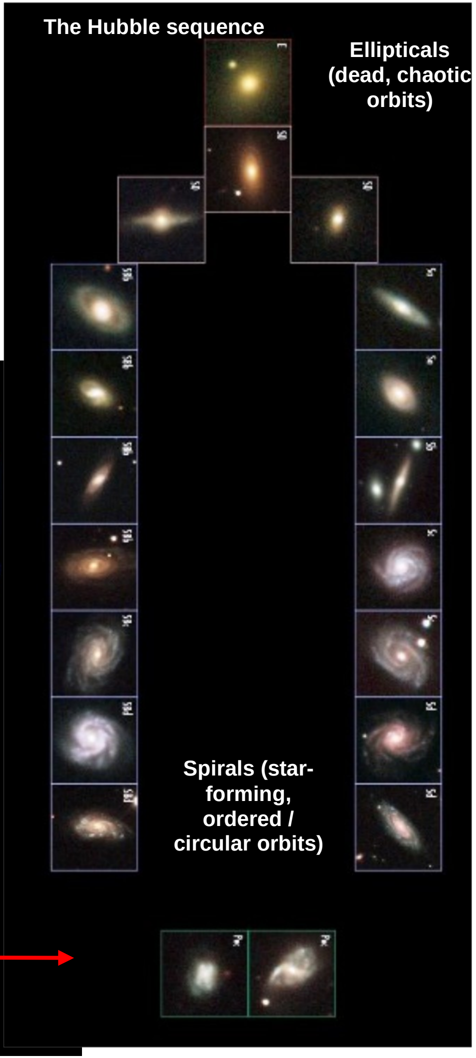
2) Low-mass, low-luminosity galaxies that serve as the building blocks of larger galaxies and preponderate these tidal features







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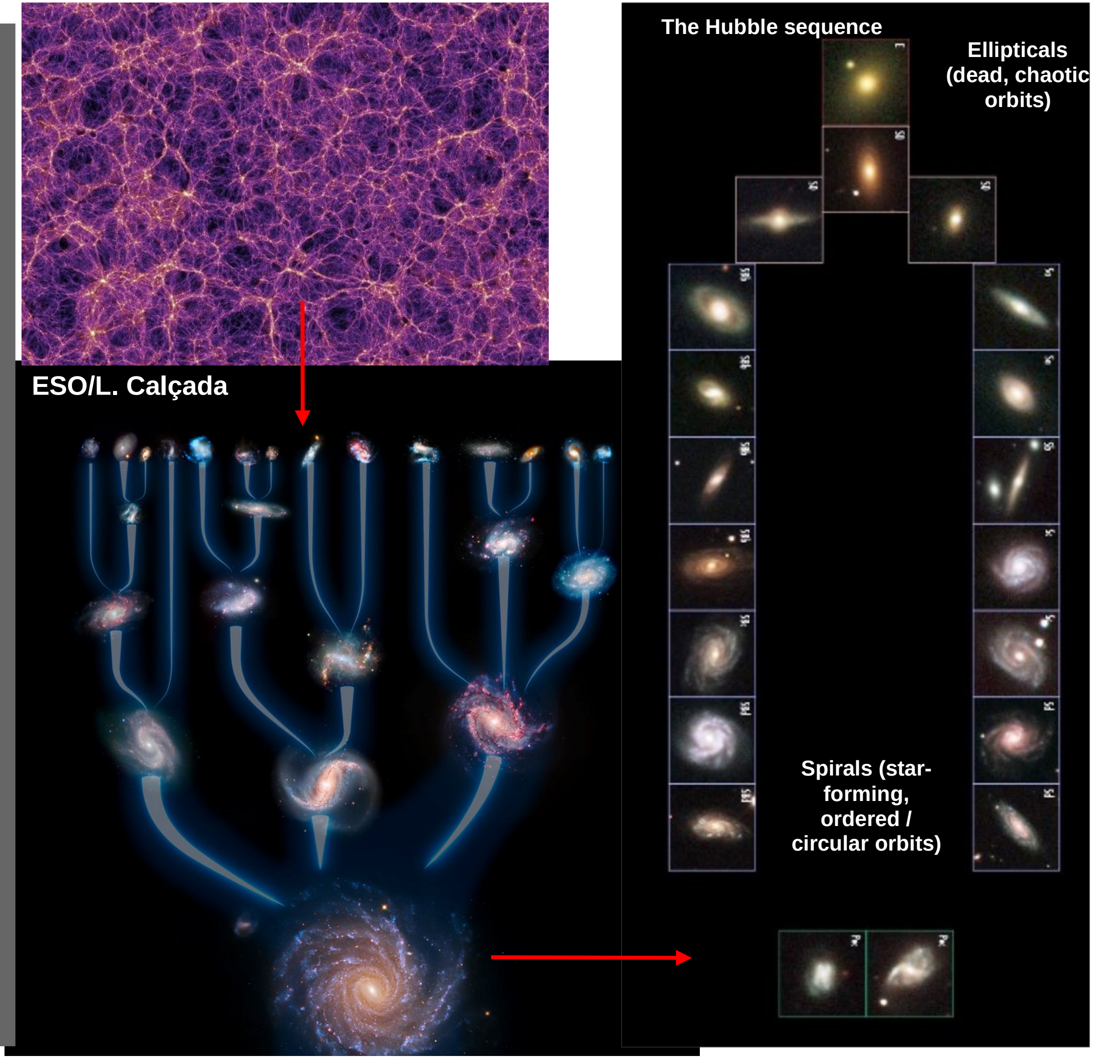
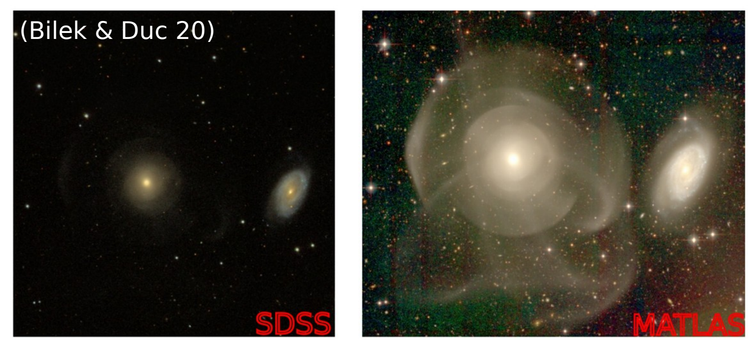
These objects enable the study of how the diversity of galaxy properties and structure emerged in the present-day Universe in the context of the cosmic structure in which they are embedded.



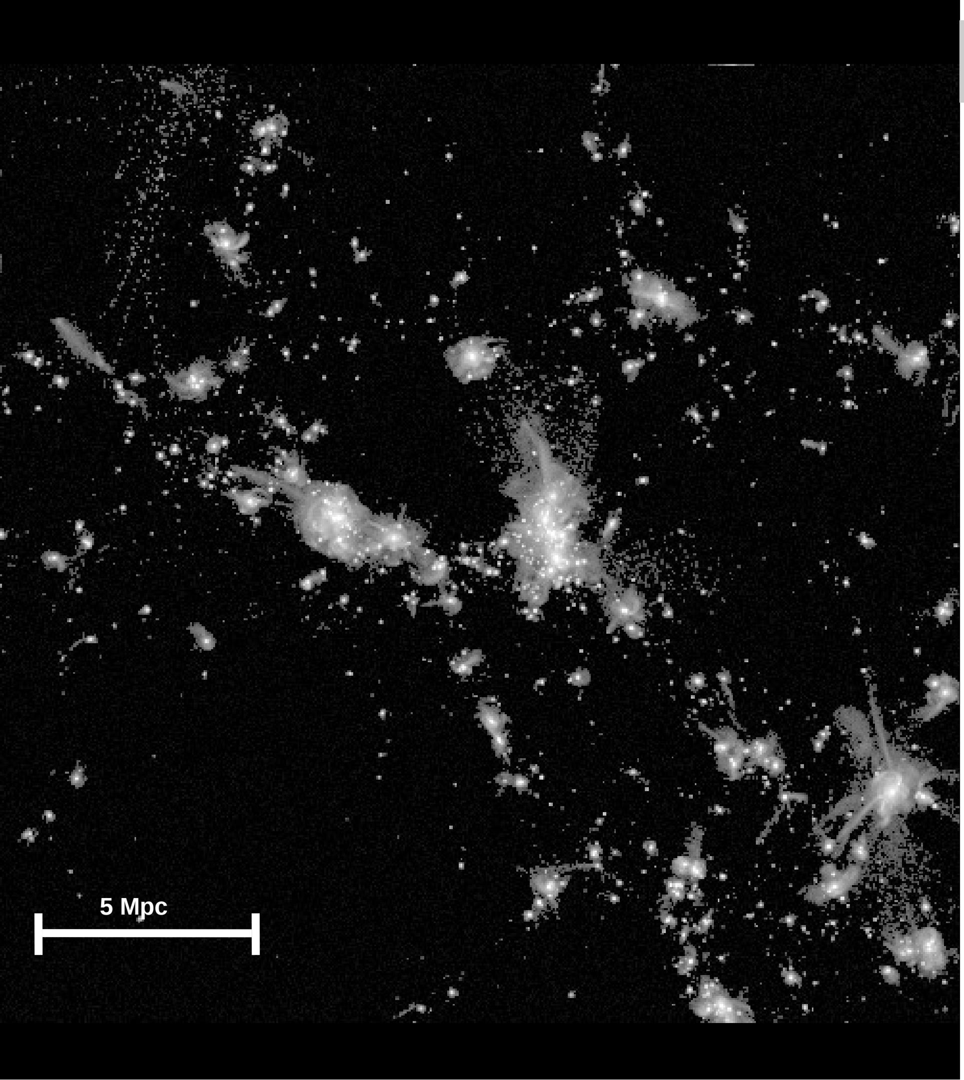
THE LOW SURFACE-BRIGHTNESS UNIVERSE

Duc+14



(Bilek & Duc 20)

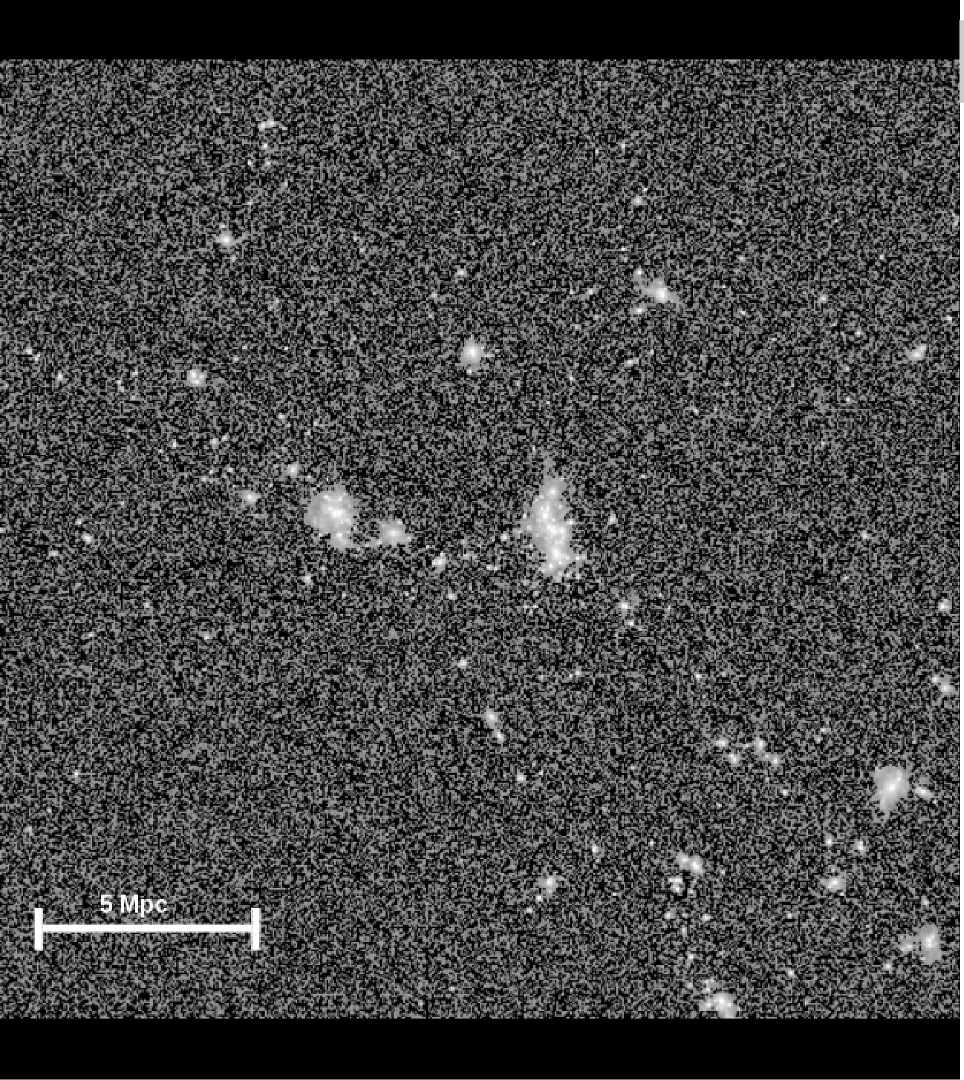
- Most of these objects lie in the low-surface-brightness regime
- The low surface-brightness (LSB) Universe is a key region of parameter space for testing our current cosmological models as well as a key probe of fundamental physics and astrophysical processes:
    - Galaxy **assembly and hierarchical structure formation**
    - Galactic archaeology
    - ‘**Missing Satellite**’ problem (**Kauffmann+93**)
    - ‘**Too Big to Fail**’ and ‘**core-cusp**’ problems (**Boylan-Kolchin+12, De Blok 10**)
    - Probe of large scale structure (e.g. **Müller+17**)
    - Probe of **fundamental physics**
        - Gravity (e.g. **Renaud+16**)
        - Dark matter (e.g. **Dubinski+96, Geringer-Sameth+15**)
    - Stellar (e.g. **Dekel+Silk 86**), AGN (e.g. **Reines+13, Kaviraj,Martin+Silk 19**) and UV **feedback** (e.g. **Rees+86**)
    - ...



THE LOW SURFACE-BRIGHTNESS UNIVERSE

- We always observe the Universe at **finite depth**
  - The objects and structures that we detect are a **biased subset** of the true underlying distribution
  - Most of these structures **lie far below SB limits achievable by contemporary surveys** (e.g. **Impey+1988**)

- Simulations help us to **inform our search** into unexplored corners of parameter space



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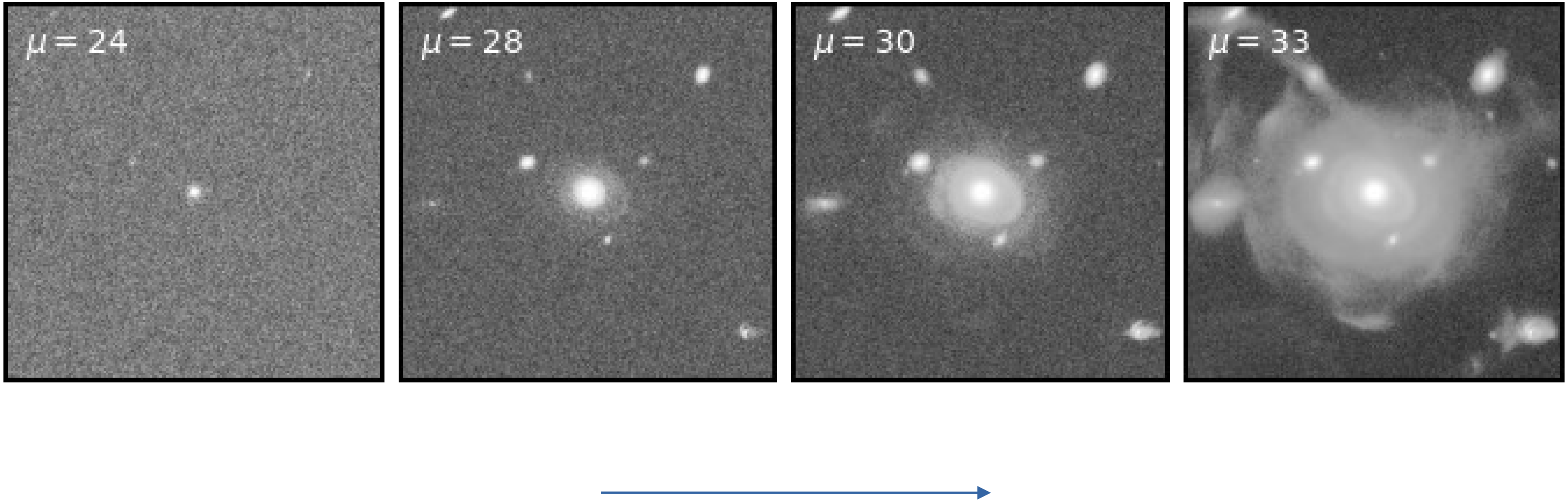

$\mu = 24$
$\mu = 28$
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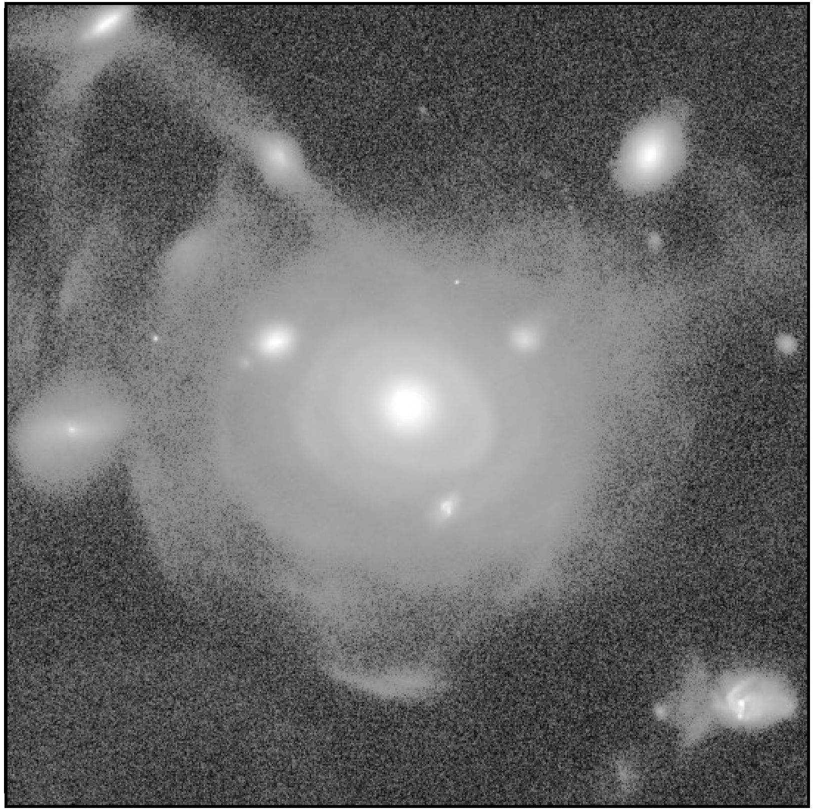
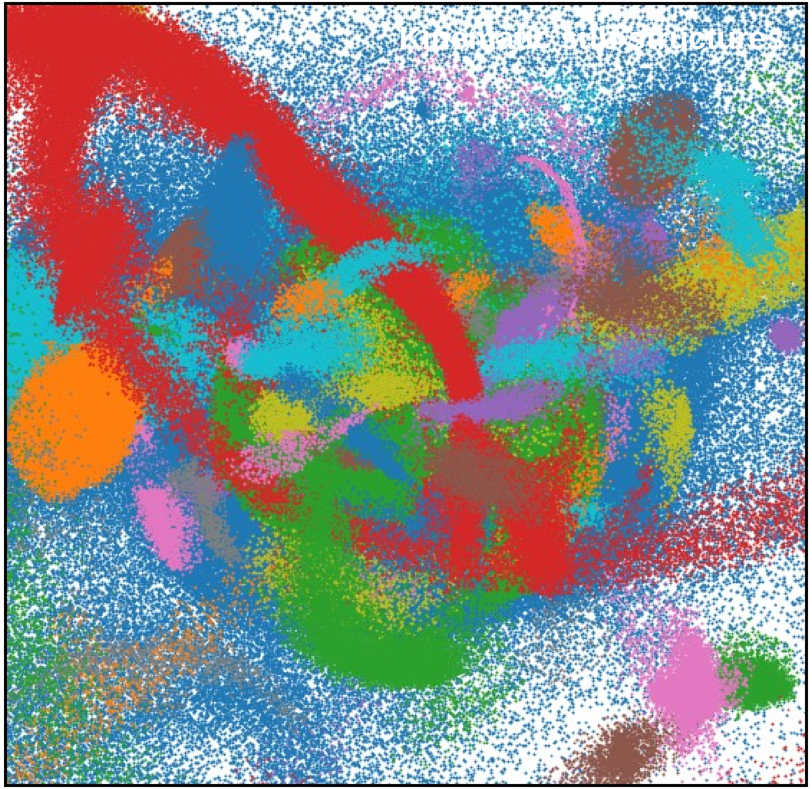
$\mu = 33$

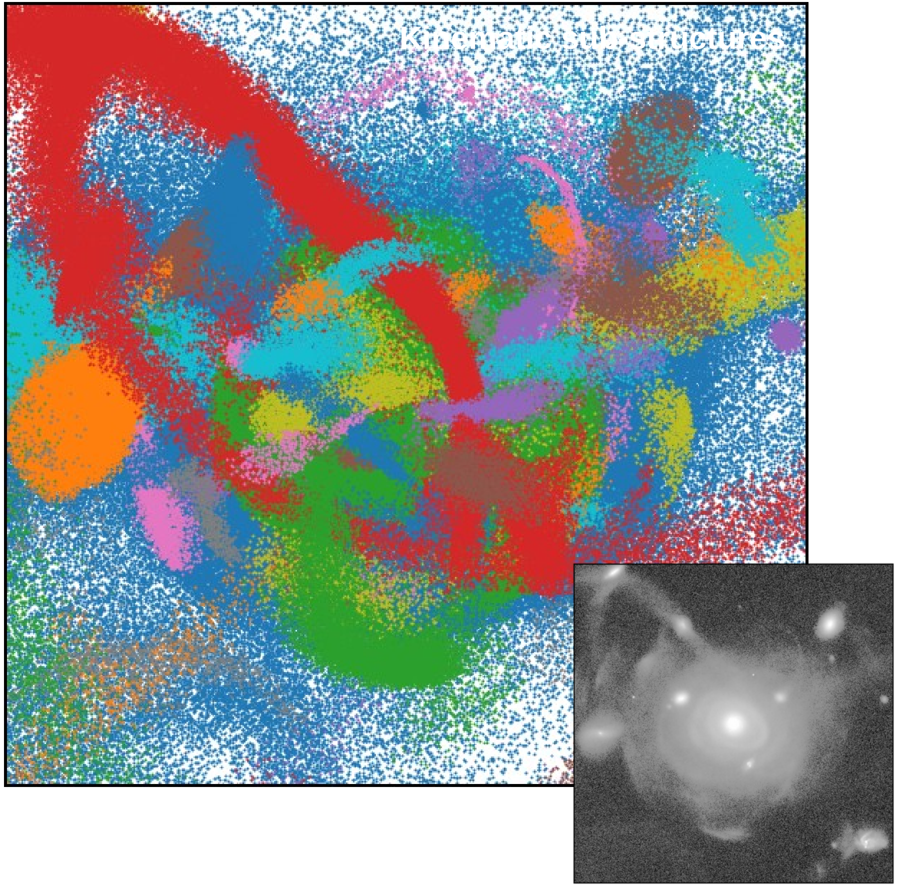



Kinematic sub-structures

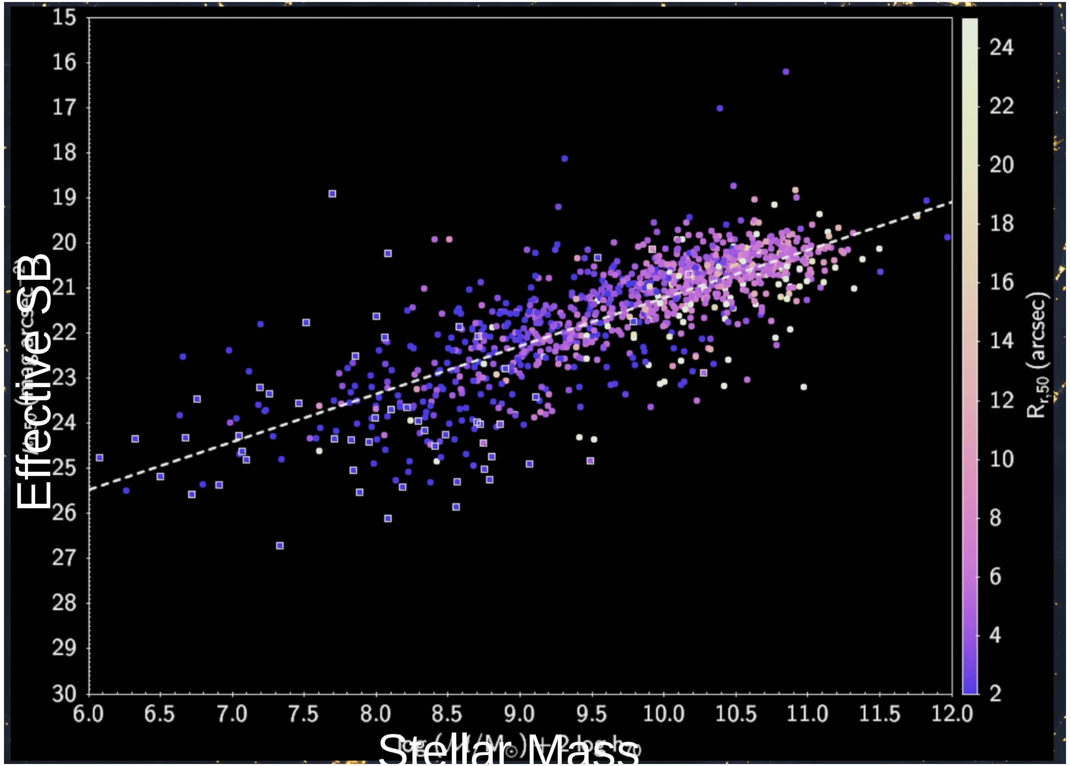
A framework for recovering galaxy assembly histories

Tidal sub-structure allow us to access a uniquely detailed record of how each galaxy has evolved over cosmic time.

- Place constraints on our current cosmological models (tidal stream abundances and properties).



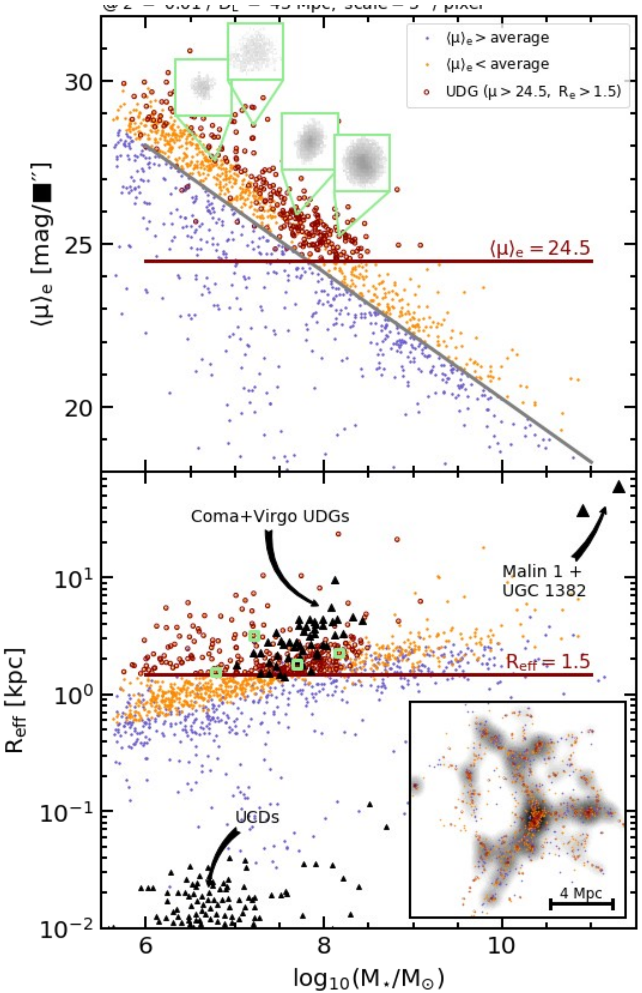
Many of the progenitor galaxies of these features may also be invisible

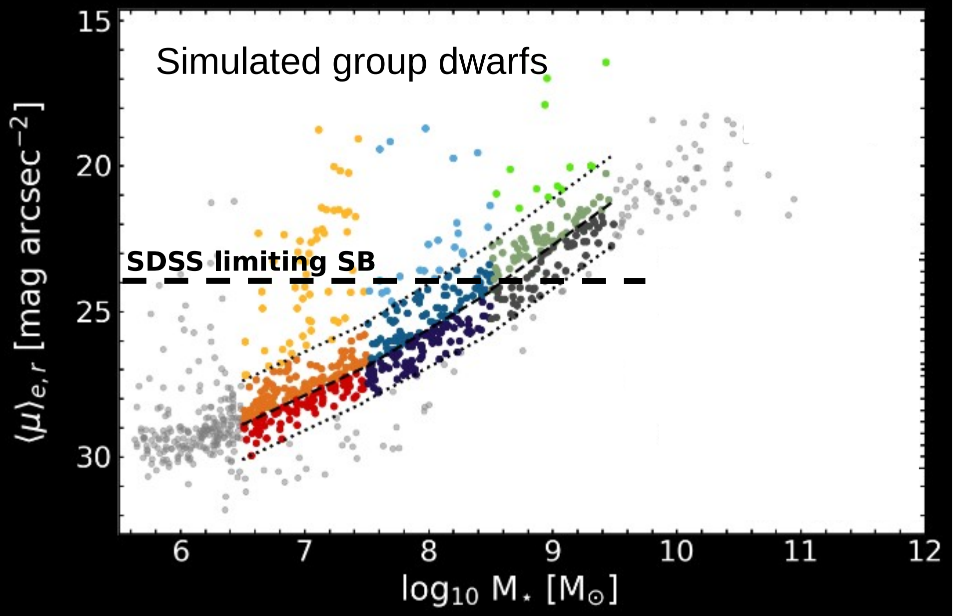


Sedgwick+(2019)
(Bothun+97)

(CCSNe selected)

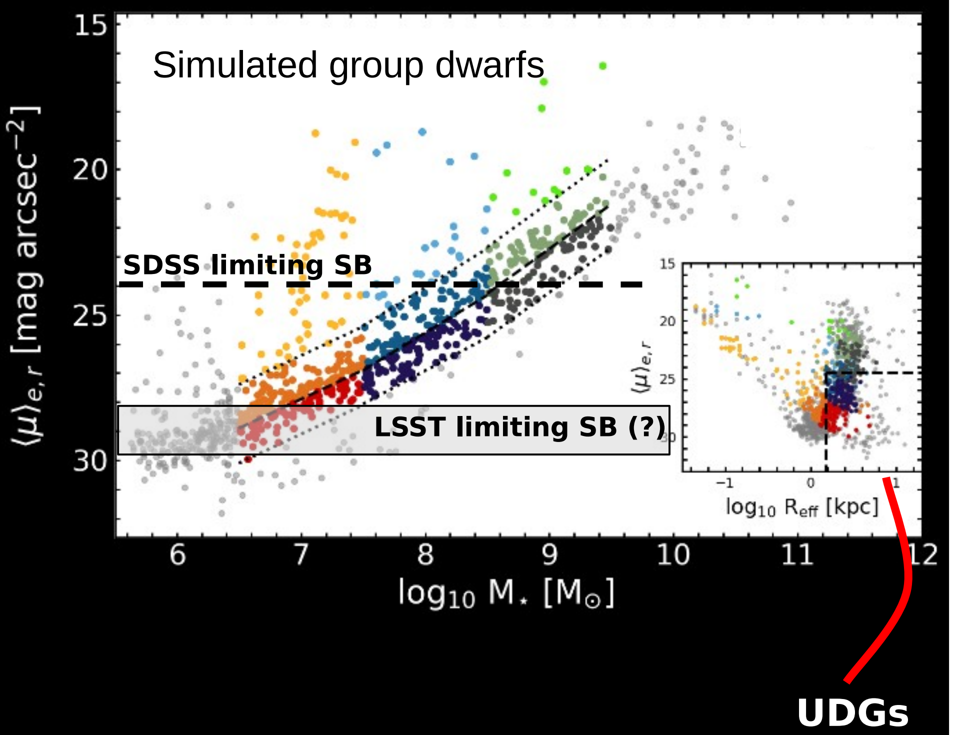
Simulations





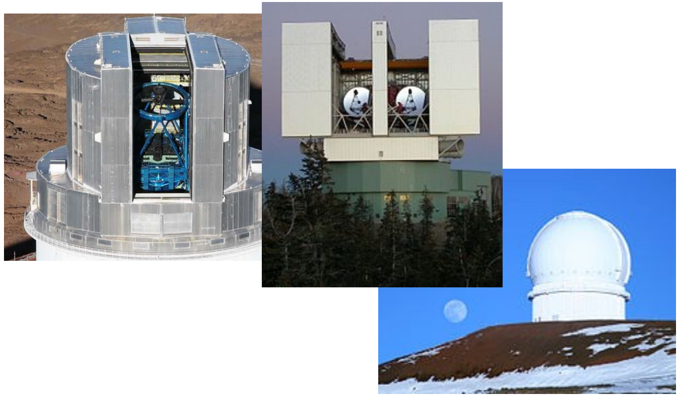
Jackson+2021 MNRAS, 502, 3

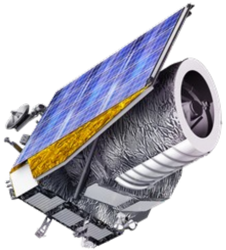
- At SB limits achievable by LSST, we can expect to be able to detect the main locus of dwarf galaxies
  - **only extreme outliers are detected in simulated SDSS** imaging (main galaxy sample)



Jackson+2021 MNRAS, 502, 3

- At SB limits achievable by LSST, we can expect to be able to detect the main locus of dwarf galaxies
    - **only extreme outliers are detected in simulated SDSS** imaging (main galaxy sample)
    - A majority of dwarfs may have effective surface brightnesses and effective radii **fitting the definition of ultra-diffuse galaxies** (UDGs)



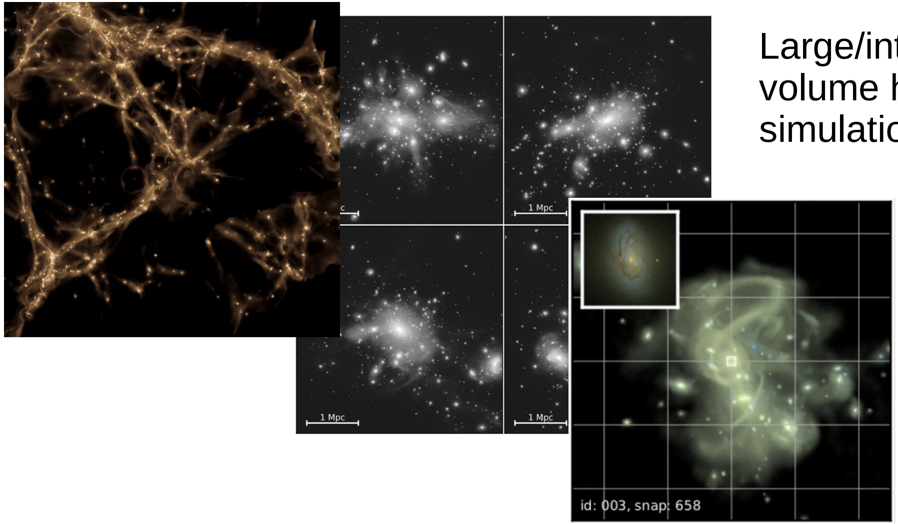


Euclid: Launch 2023, DR1 by 2025

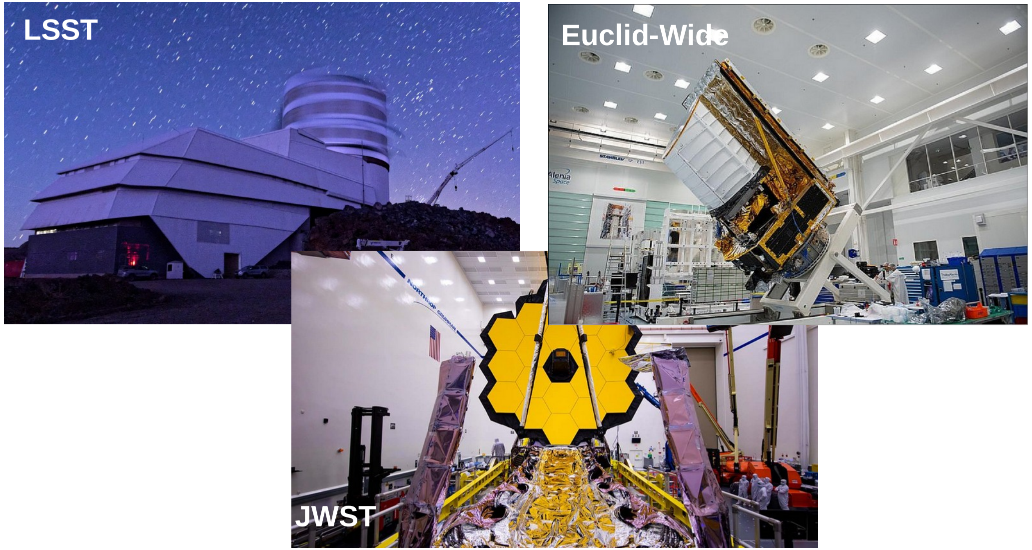
JWST: COSMOS-Webb + PANORAMIC in 2023 (+ resolved population studies)

Rubin: LSSTCam on-sky by early 2024, DR1 by 2025

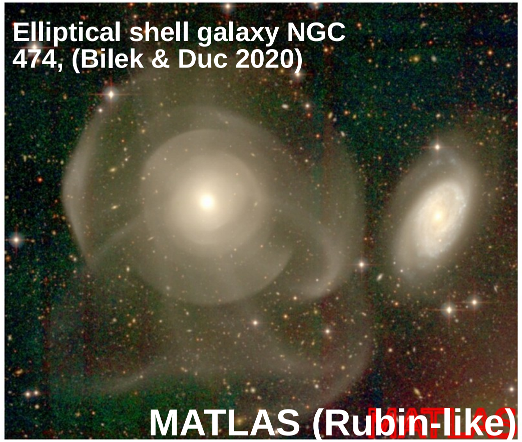
Existing and upcoming deep small-to-medium area surveys including CFIS, LIGHTS, HSC-SSP



Large/intermediate volume high-resolution simulations



Past surveys

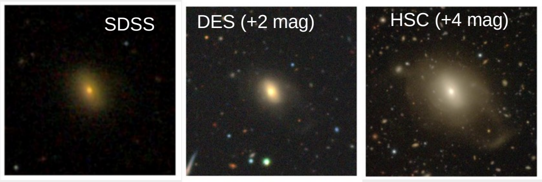


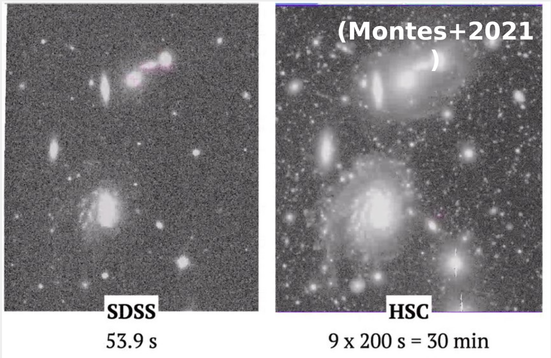
Current state-of-the-art

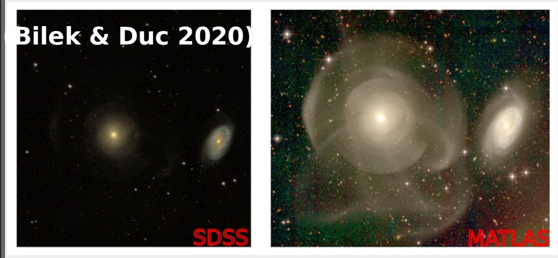
Deep-wide imaging from Rubin/LSST, Euclid-Wide and JWST (COSMOS-Webb and PANORAMIC) will allow us to move beyond the limitations/biases of past wide surveys (e.g. SDSS) which were only sensitive enough to probe the central parts of the brightest galaxies.

Deeper imaging for billions of galaxies will reveal many intricate structures, which are powerful indicators of the processes that drove their evolution.

Enabling a much less biased understanding of galaxy populations at key epochs their evolutionary history



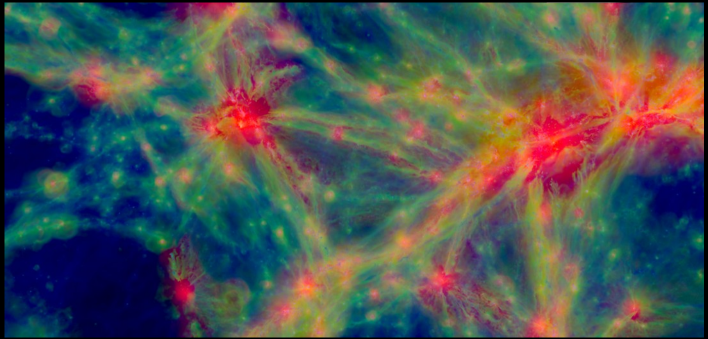




Deep imaging in the era of the Rubin Observatory/LSST

- Rubin Observatory pathfinders like Subaru / Hyper-SuprimeCam provide similar quality imaging to that expected from the VRO ($\mu^{lim}_{r}(3\sigma,10''\times10'') > 30$ mag arcsec^{-2})
  - HSC shows us that the Rubin Observatory will be capable of recovering many more LSB features around galaxies

- For LSB science, the main advantage of the Rubin Observatory is the much larger sample size
  - In anticipation of these much larger samples, it is useful to be able to produce detailed predictions under ΛCDM
    - Frequency and distribution of tidal features as a function of halo mass
    - Detectability of tidal features

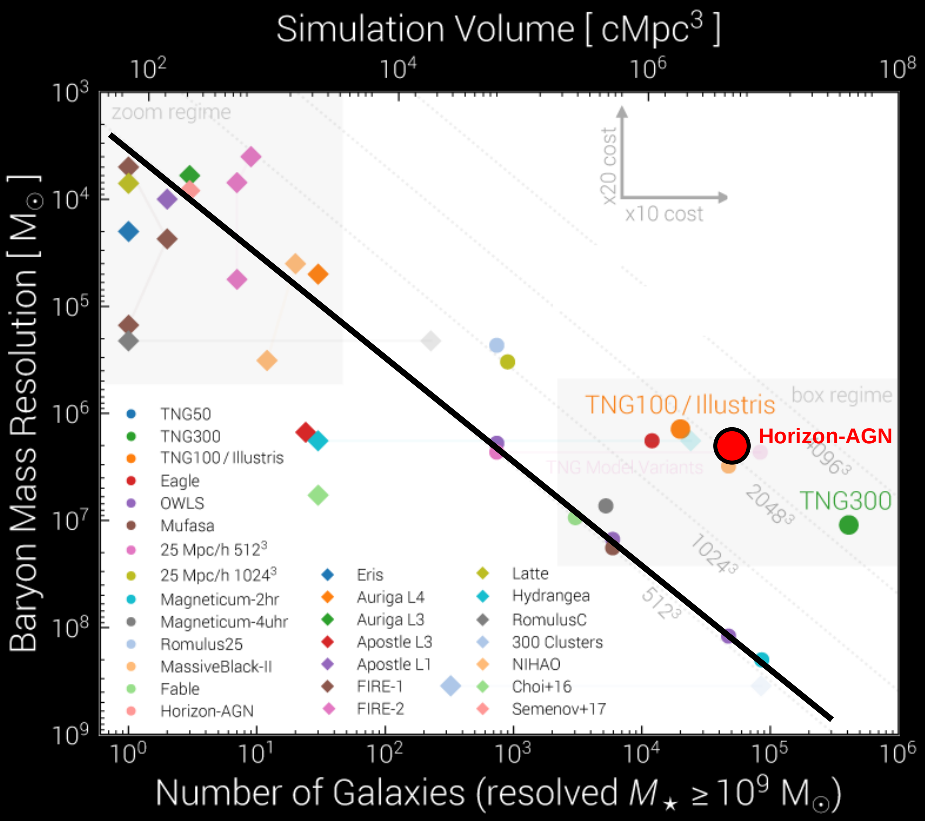


EAGLE cosmic web, image through the Horizon-AGN light cone, mock images of individual Illustris galaxies

Past hydrodynamical simulations

- A compromise between volume and detail
  - Zoom-in simulations focussed on individual haloes (e.g. NIHAO, FIRE, RomulusC)
  - Or on large volumes simulated at coarse resolutions (e.g. Eagle, Massive-Black, Horizon-AGN, Illustris etc)

- Adequate for the era of SDSS where only high surface brightness objects are accessible
  - Statistical low surface-brightness studies are limited due to mass resolution
  - Spatial resolution not sufficient to resolve the effective radii of dwarfs



Adapted from plot by Illustris collaboration

CURRENT STATE OF THE ART

- It is becoming possible to simulate **large volumes at higher resolution** — allowing intermediate volume simulations with resolutions comparable to high-res zoom-ins (e.g. **New Horizon, Romulus25 and Illustris TNG-50**):

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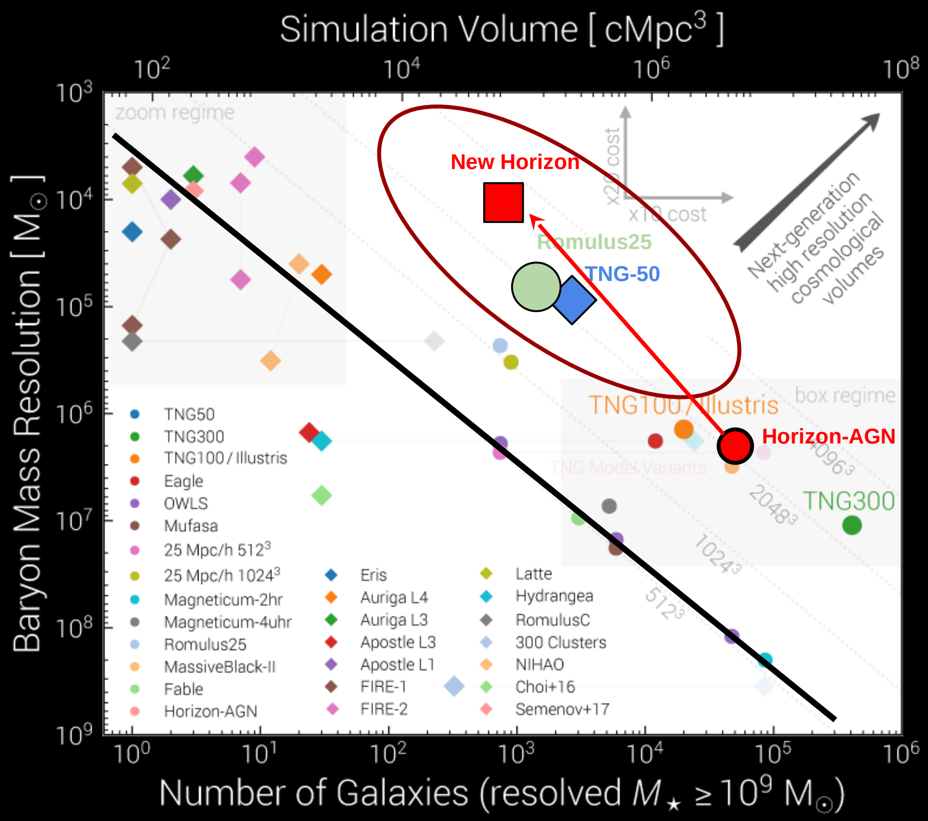

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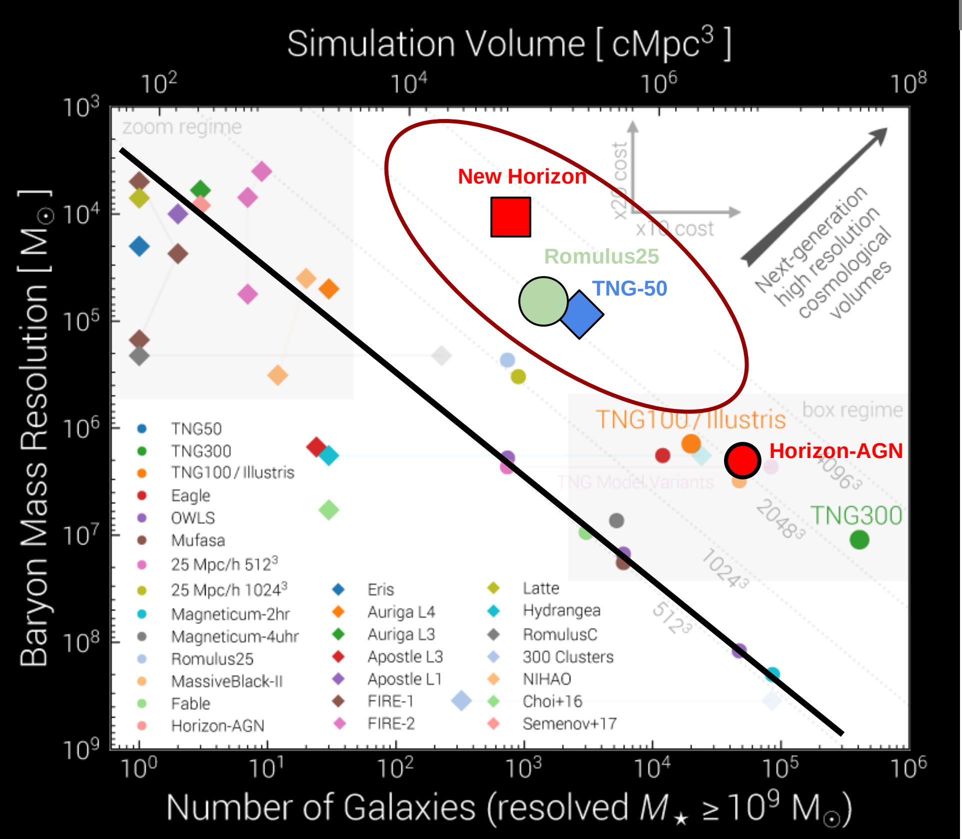

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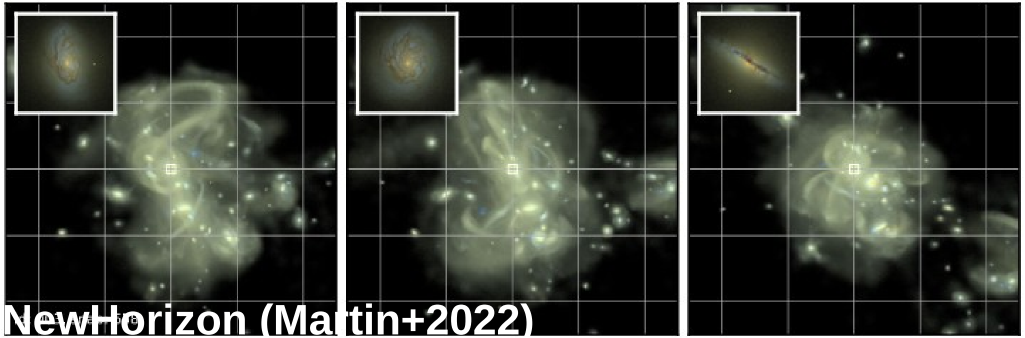
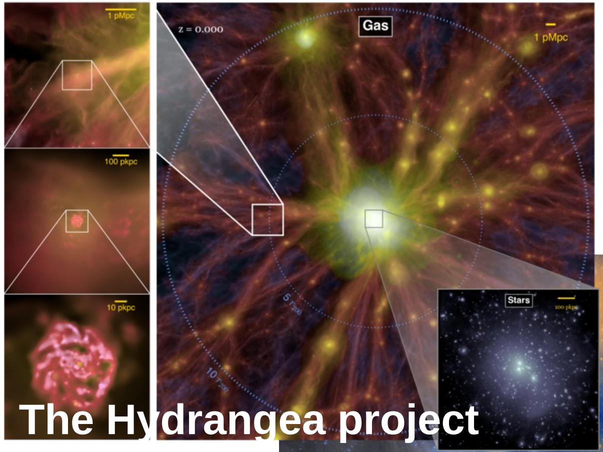
    - Spatial resolution from 10s to 100s of parsecs
    - Mass resolution from 10^4 - 10^5 Msun
    - Volume > 10^5 Mpc^3
    - Large enough volume for **statistical studies** to be possible
    - High resolution enables studies of the detailed properties of **individual LSB dwarf galaxies** and the **LSB outskirts** of massive galaxies, ICL etc
    - Desirable compared to many single halo zoom-in simulations because the larger **cosmological context** (environment, interactions, cosmic web etc.) is a key part of understanding galaxy evolution
    - Limited volume compared to large box simulations introduces **uncertainty due to cosmic variance**



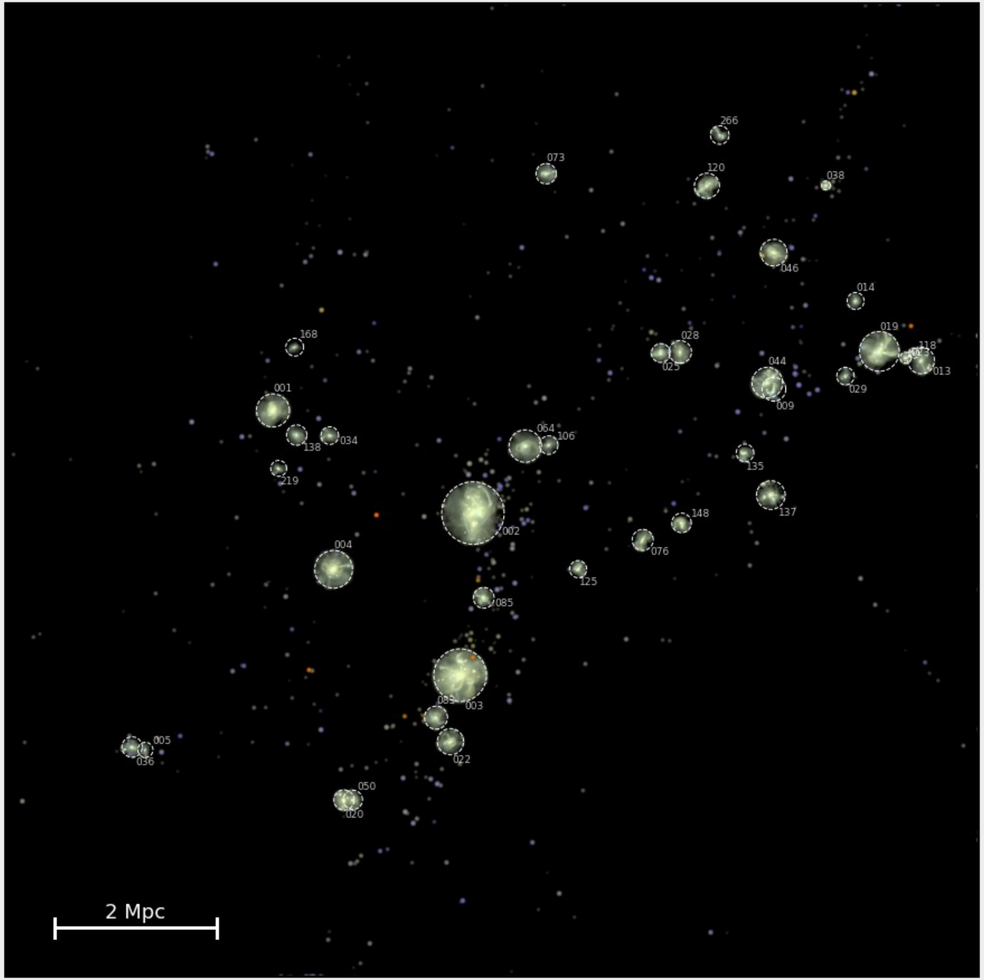


Next-generation simulations are reaching parity with the capabilities of new surveys
- Resolving very-low mass tidal features and their progenitor galaxies.

At present, simulations cover intermediate volumes, not representative of all cosmic environments

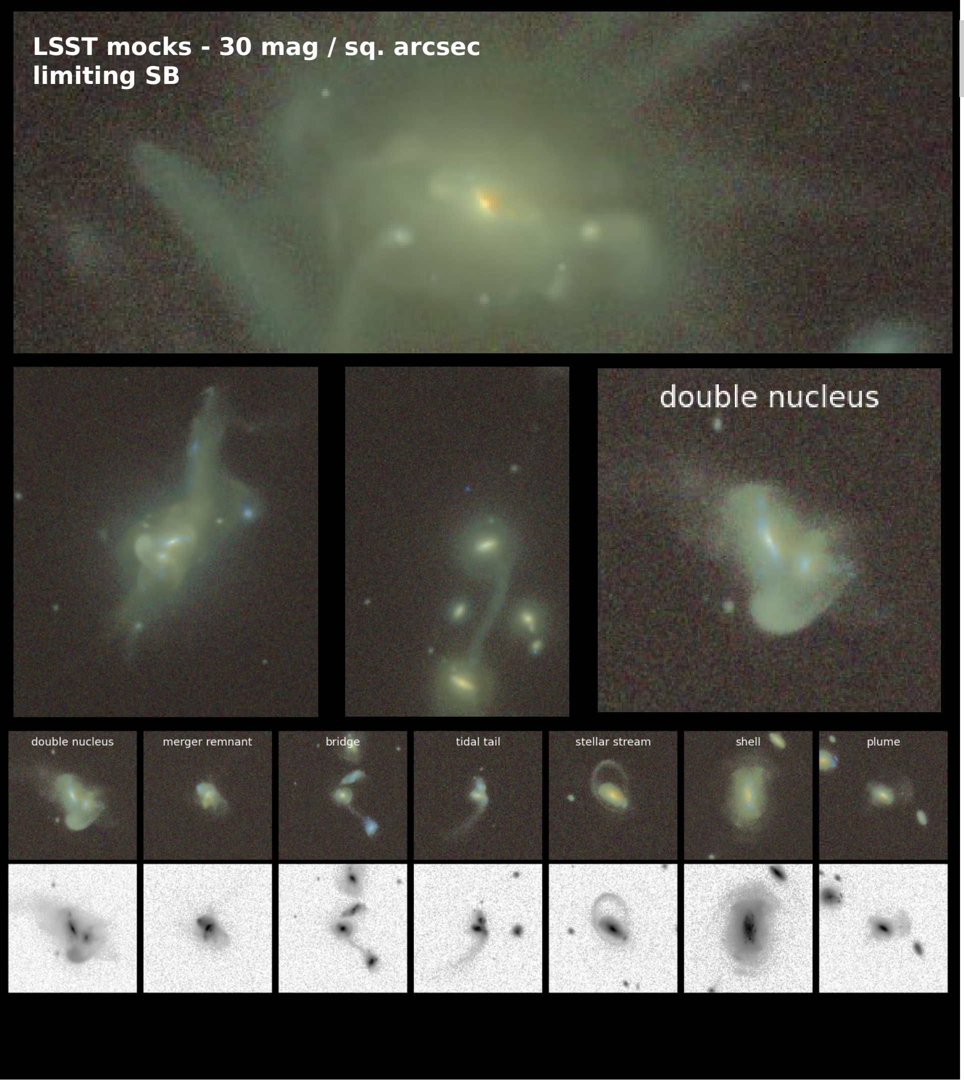
Together current and upcoming high-resolution simulations will cover a wide range cosmic environments and halo masses

MNRAS, 513, 1, pp.1459-1487, arXiv:2203.07675



The New Horizon Simulation (Dubois+21)

- **New Horizon is a high resolution cosmological simulation**
  - Contiguous volume of (16 Mpc)^3
  - High spatial and stellar mass resolution of **34 pc / 10^4 M$_\odot$**
  - Sufficient mass resolution to resolve the satellites and stellar halo around <MW mass galaxies



CURRENT WORK: TIDAL TAILS AND ICL

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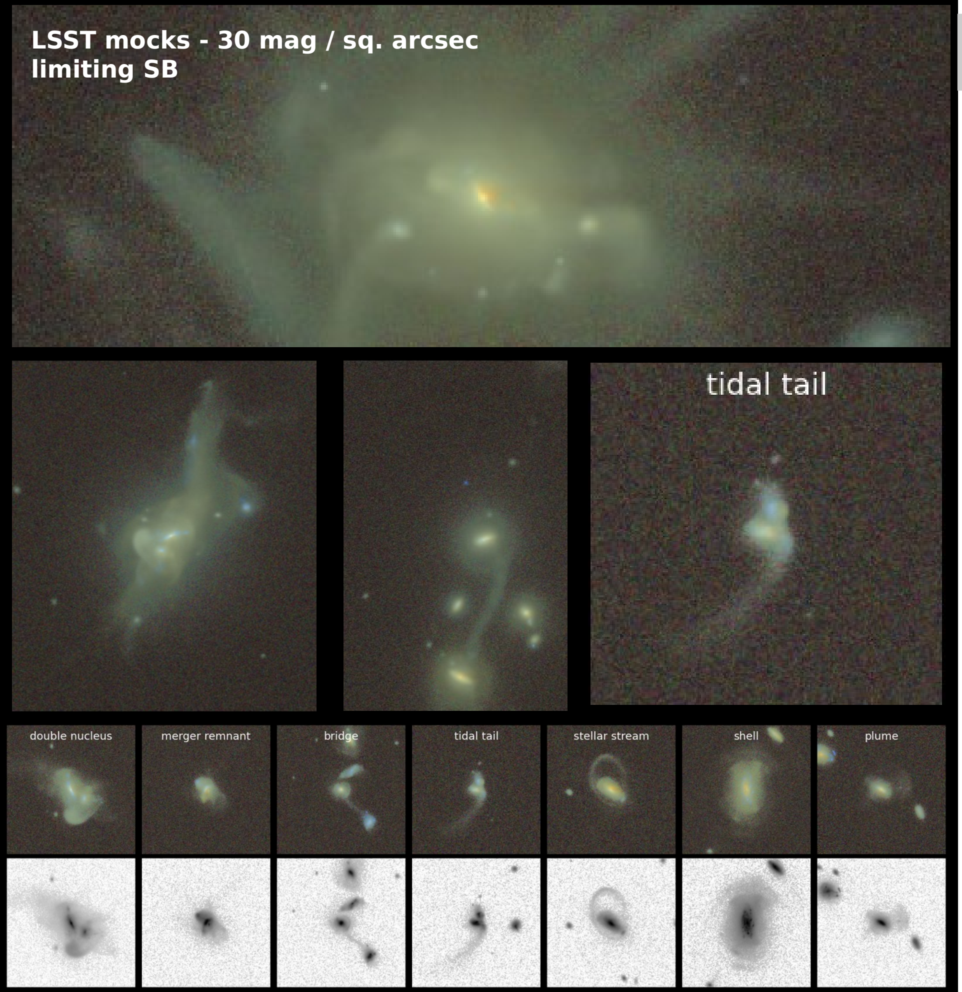

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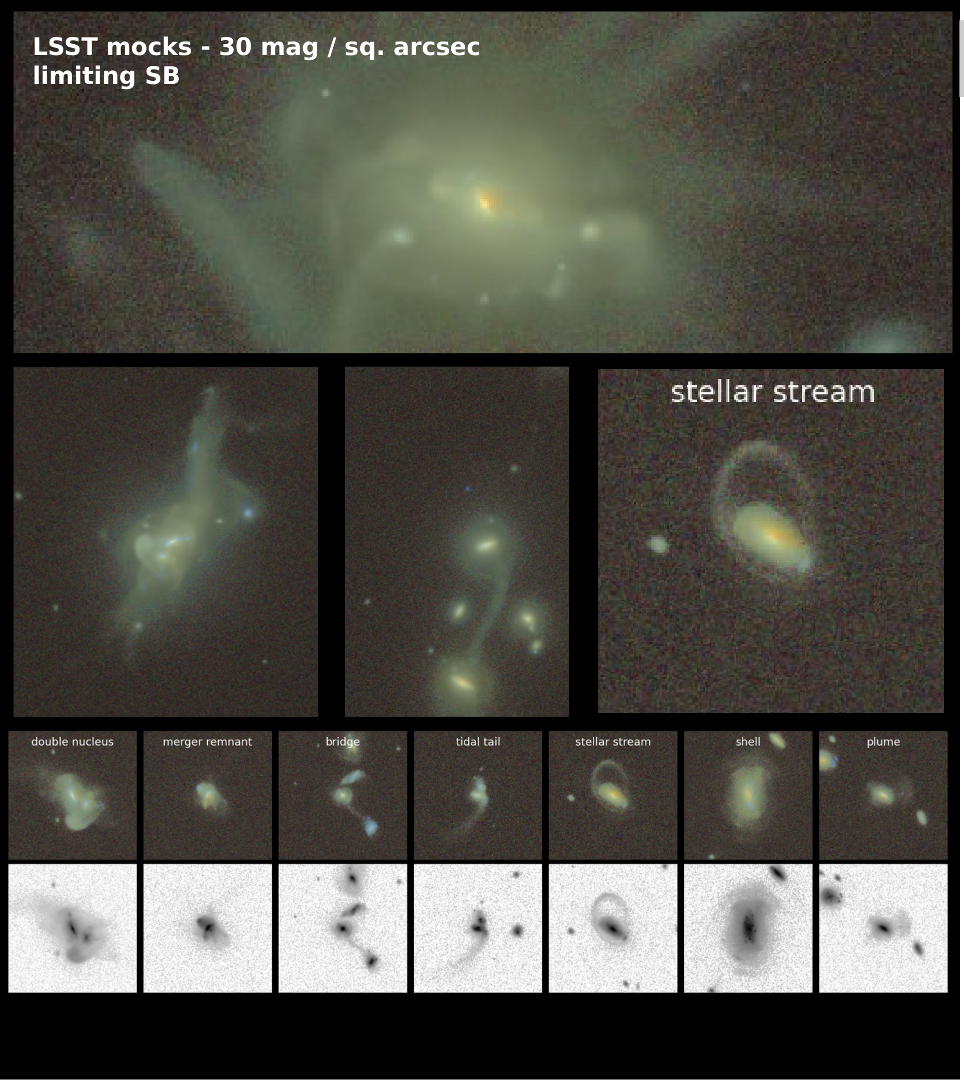

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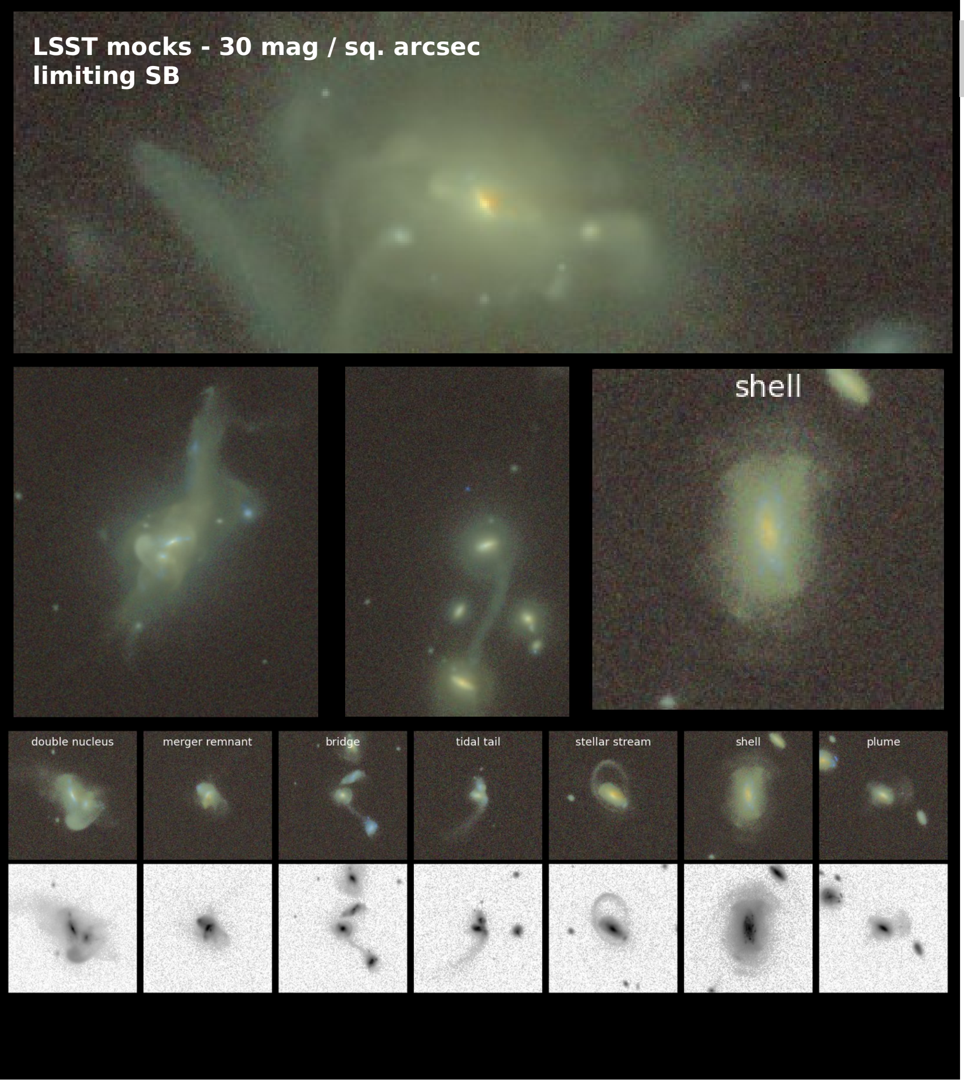

CURRENT WORK: TIDAL TAILS AND ICL

- NEWHORIZON reproduces a full range of expected tidal features
- We can use our mock images to make detailed ΛCDM predictions that will allow us to understand the capabilities of new datasets and make predictions for:
  - **Frequency and distribution** of tidal features as a function of halo mass
  - **Biases** from orientation, redshift, etc.
  - Surface brightness distribution of tidal features

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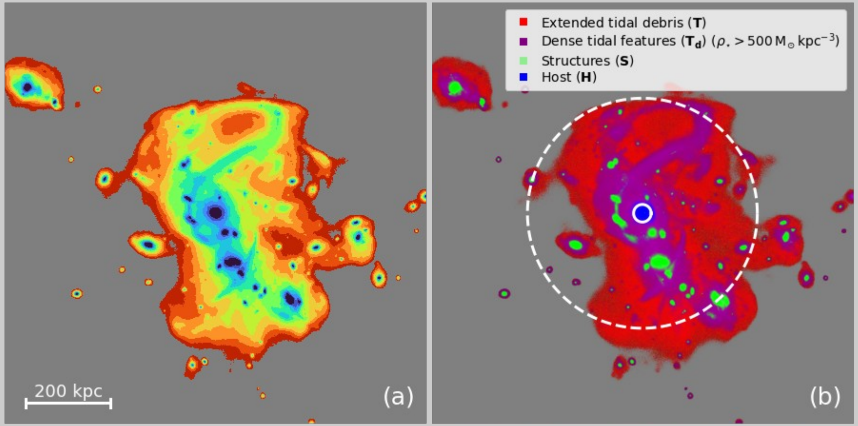
Measuring flux distributions in the stellar halo



- Decompose galaxy stellar haloes into:

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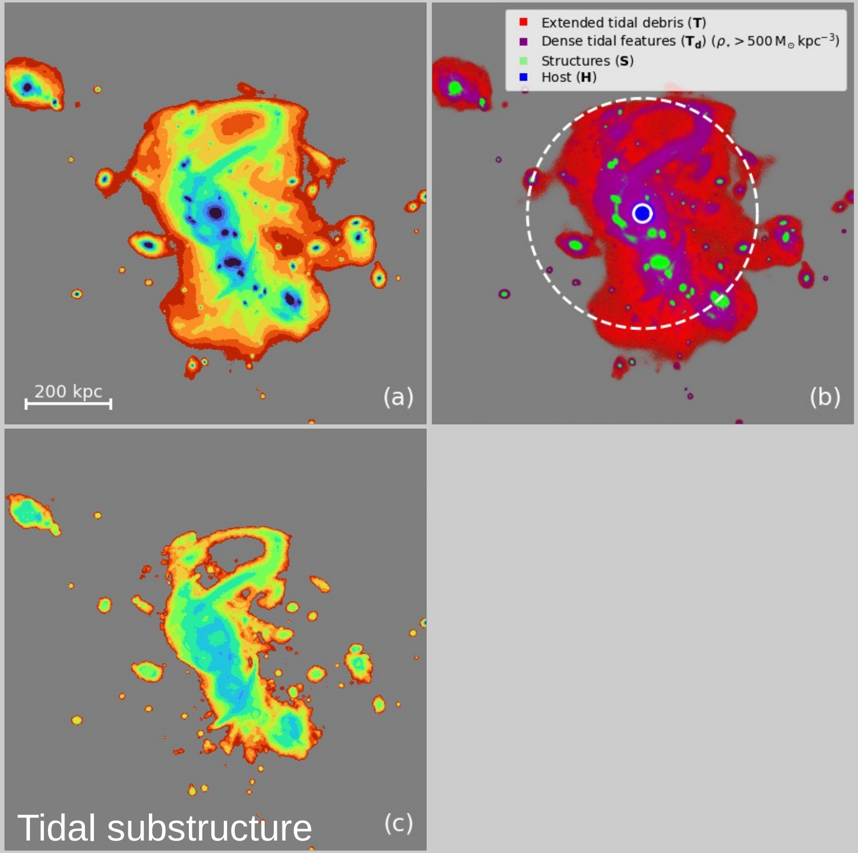

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    1) Dense tidal substructures (density cut maximising high spatial frequency features <50 kpc **Sola+2022**)

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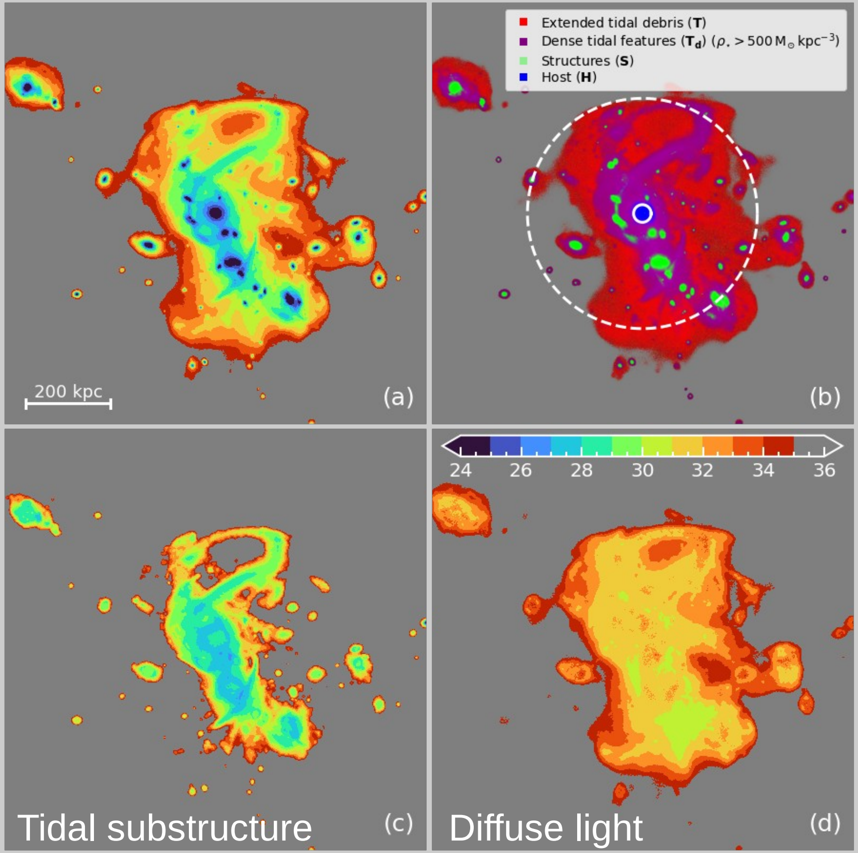
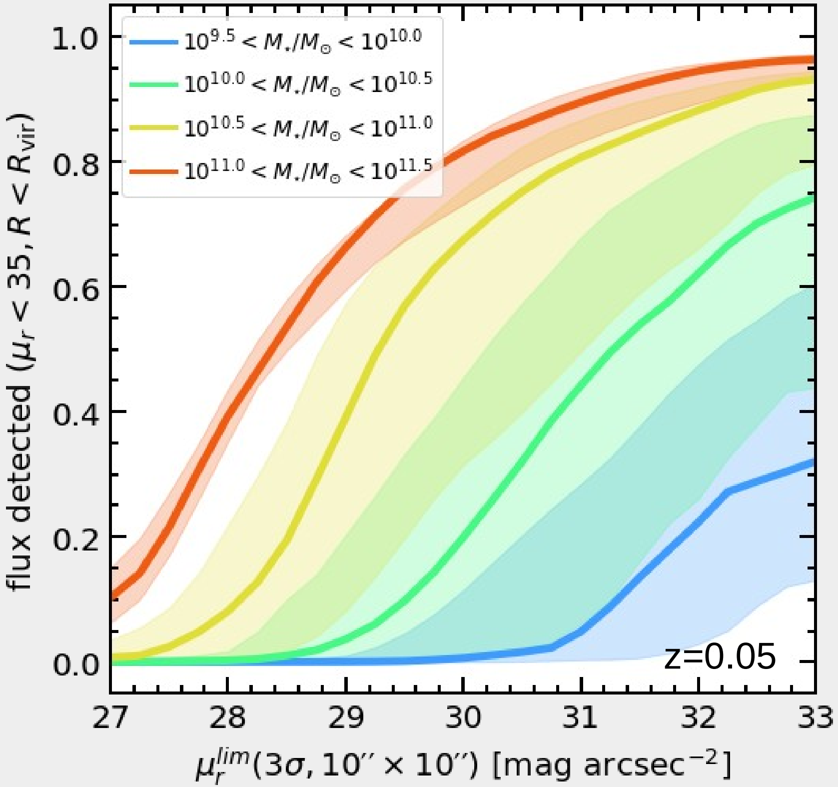
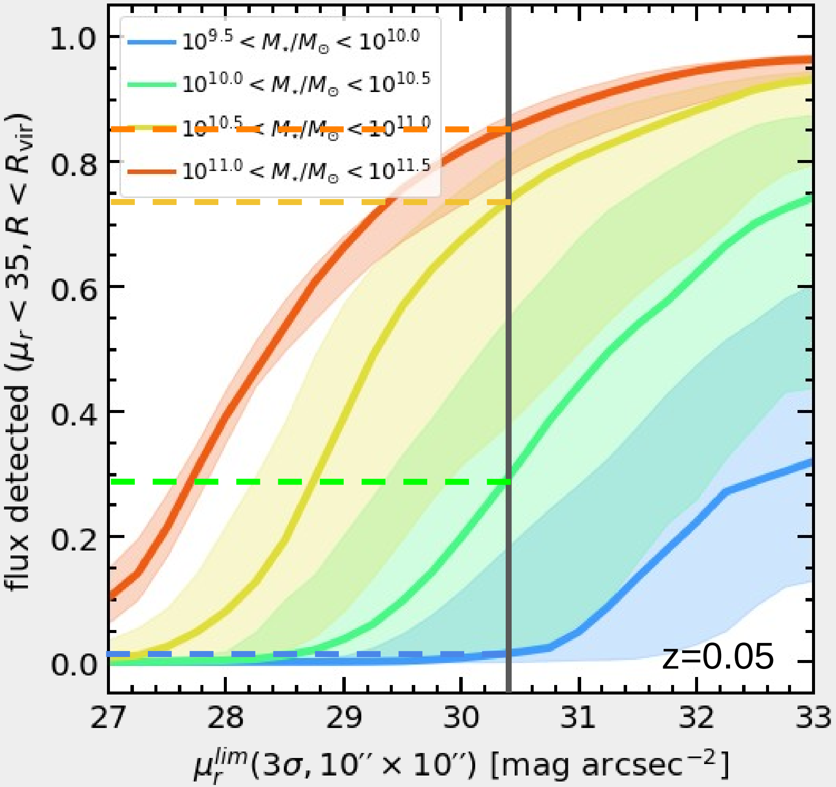


- Decompose galaxy stellar haloes into:
  1) Dense tidal substructures (density cut maximising high spatial frequency features <50 kpc **Sola+2022**)
  2) Diffuse light / debris (low spatial frequency features)



Measuring flux distributions in the stellar halo

- Lower mass galaxies ($M_*/M_\odot < 10^{10}$) are unlikely to have detectable tidal features at LSST SB limits.



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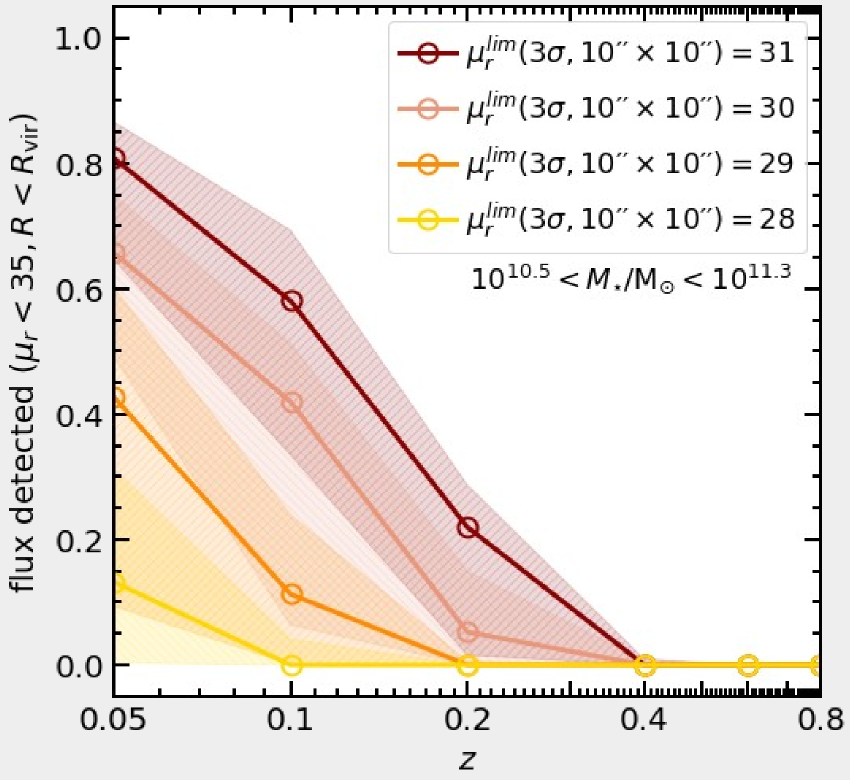


Measuring flux distributions in the stellar halo

- Lower mass galaxies ($M_*/M_\odot < 10^{10}$) are unlikely to have detectable tidal features at LSST SB limits.
- A large fraction of flux in more massive galaxies is likely to be detected
- The number of galaxies with detectable tidal features also falls with redshift so that <10% flux in the stellar haloes of MW mass galaxies is detected by z=0.2
  - The low mass / high redshift Universe will remain inaccessible

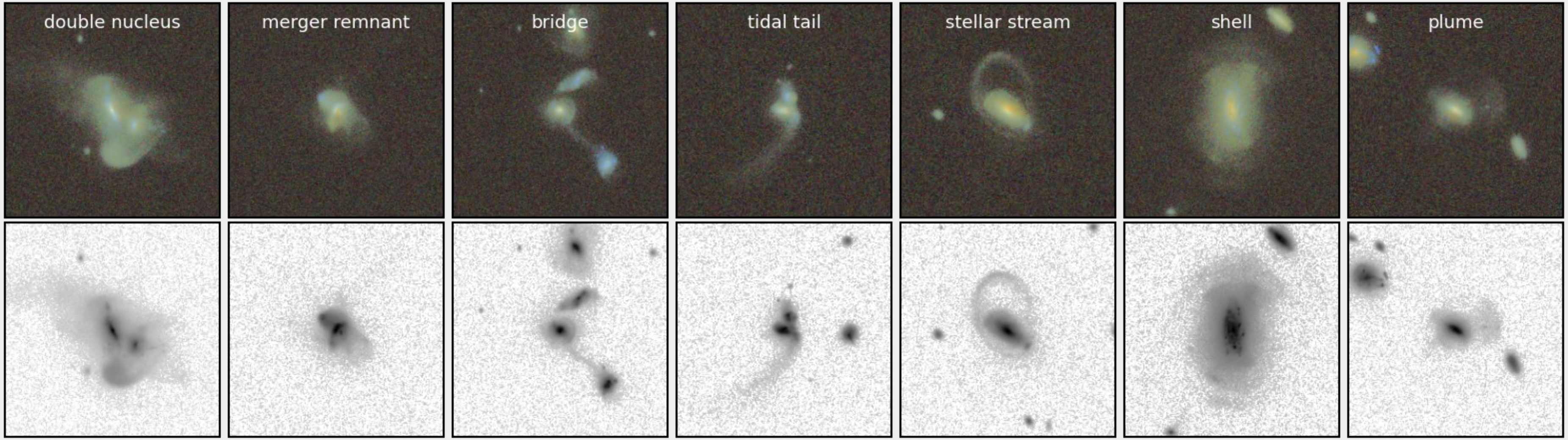
Martin+2022, MNRAS, 513, 1, pp.1459-1487, arXiv:2203.07675

Visually classifying LSB features in the stellar halo

- LSST will recover a significant fraction of flux in a wide range of stellar haloes
  - Characterising individual features will be challenging

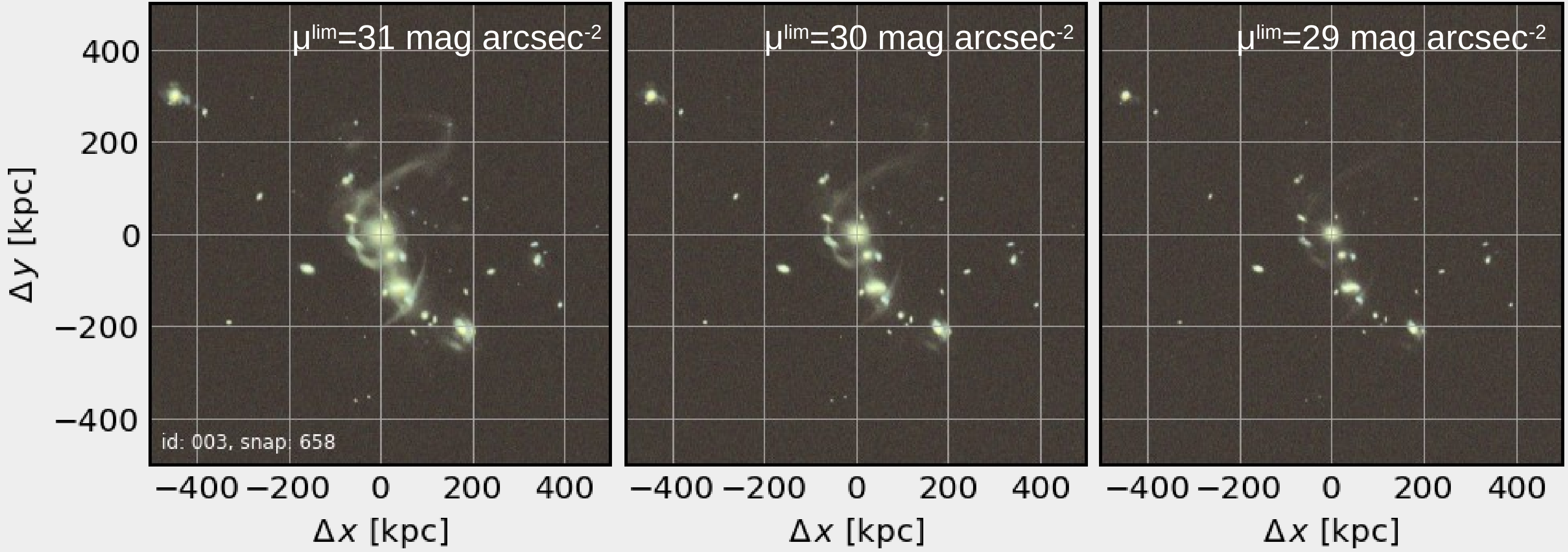
~50 volunteers visually classified tidal features mock Rubin Observatory images

- Varied limiting surface brightness (single visit → 10 year depth)
- Varied orientations



Visually classifying LSB features in the stellar halo

- Sources of uncertainty
  - Limiting surface brightness



Visually classifying LSB features in the stellar halo

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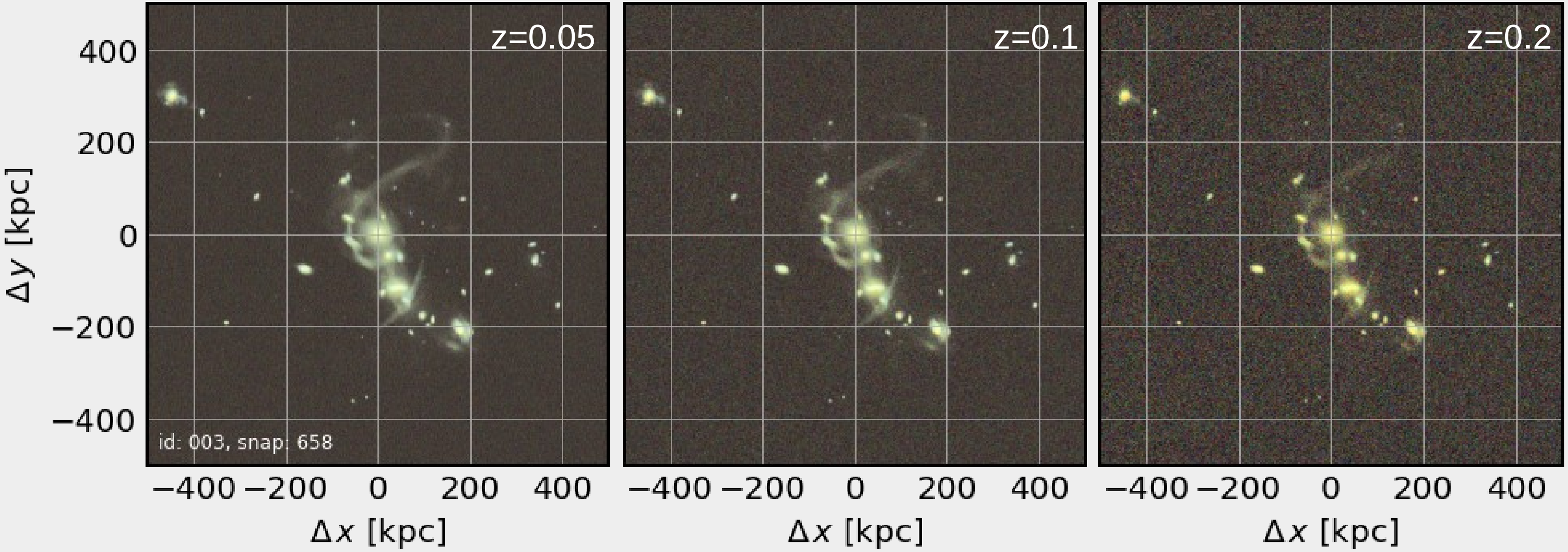
  - Surface brightness dimming and decrease in spatial resolution with redshift



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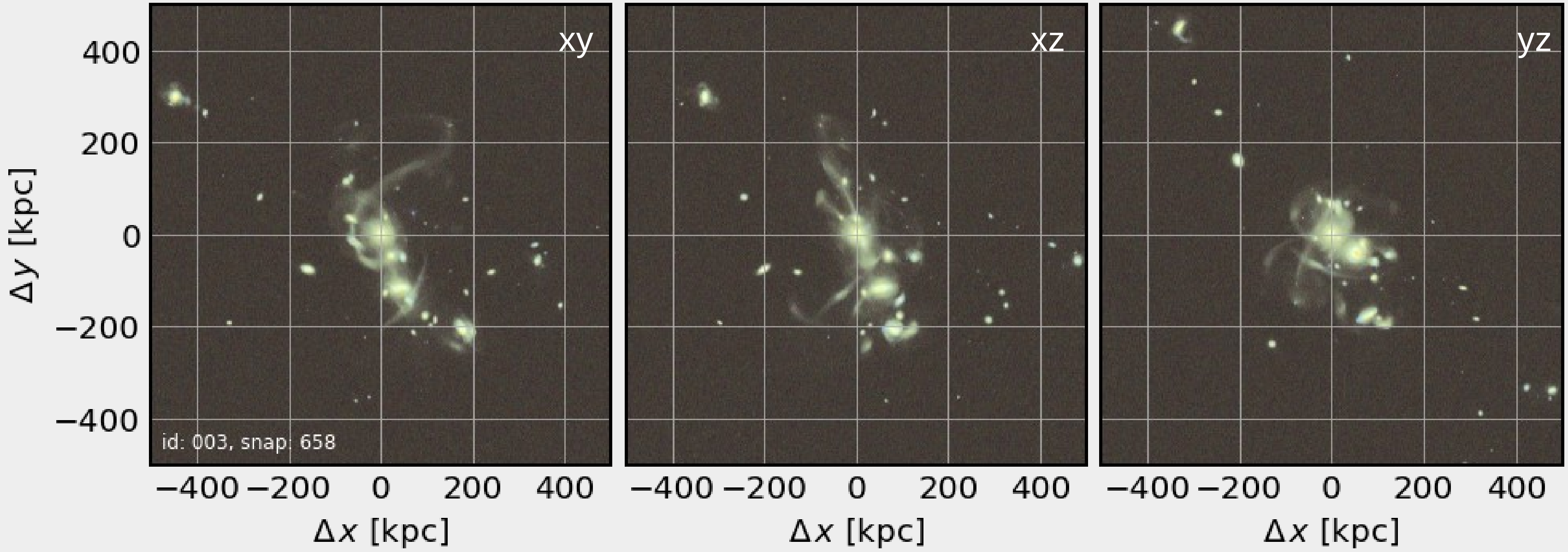
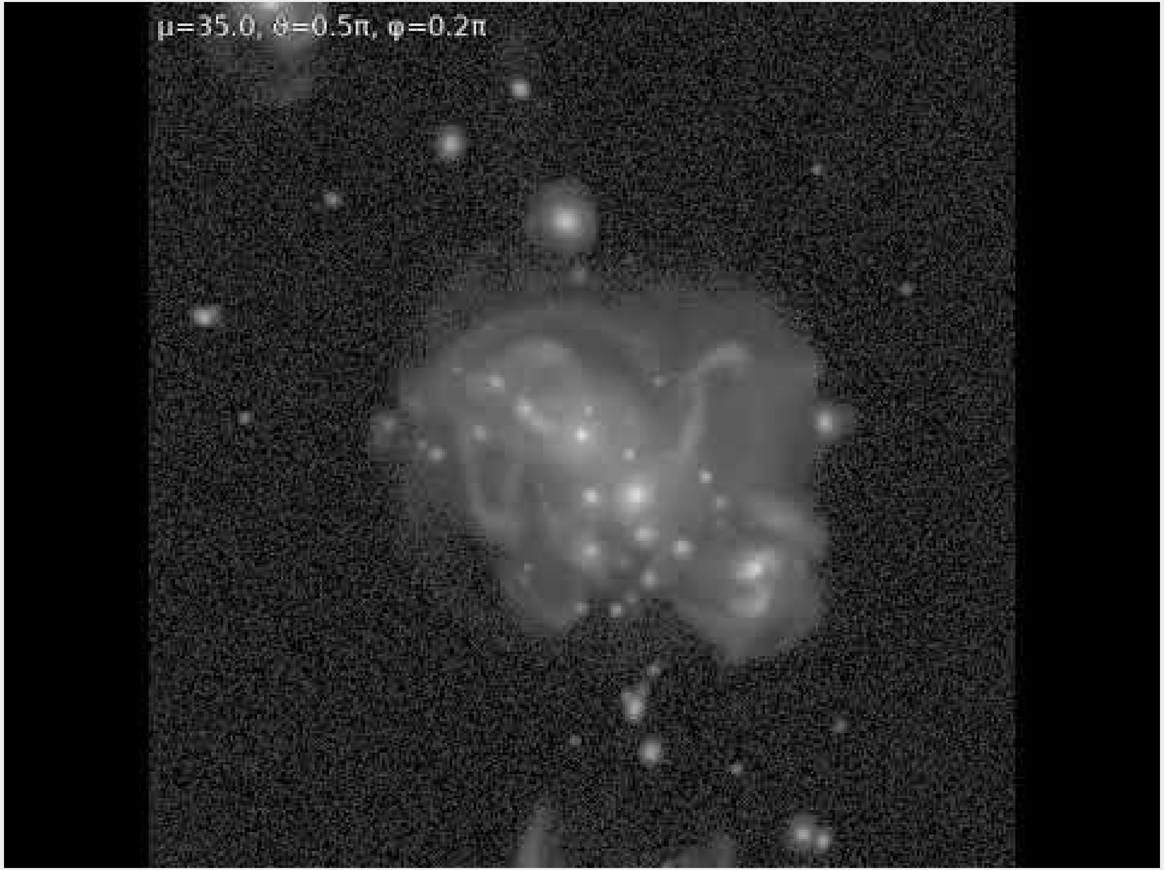


Visually classifying LSB features in the stellar halo

- Sources of uncertainty
  - Limiting surface brightness
  - Surface brightness dimming and decrease in spatial resolution with redshift
  - Orientation
  - PSF
  - Chance projection of other objects
  - Ambiguity in tidal feature classification



https://youtu.be/gPVT3AlNzHc

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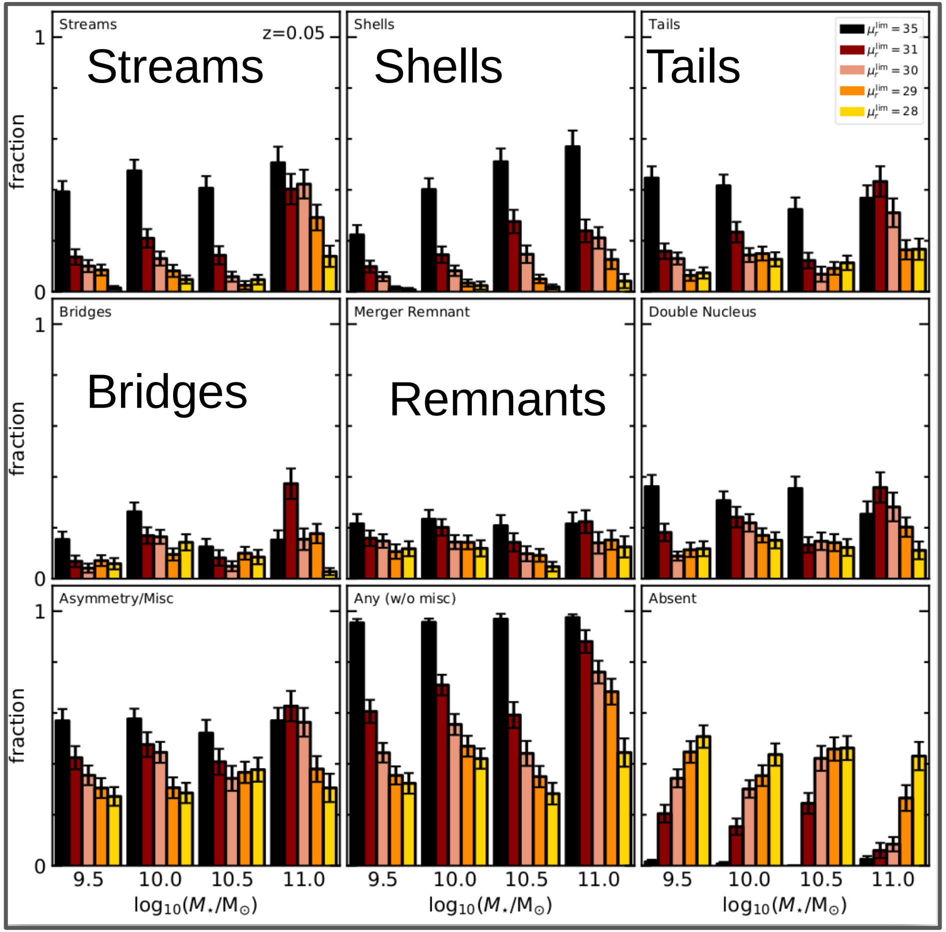
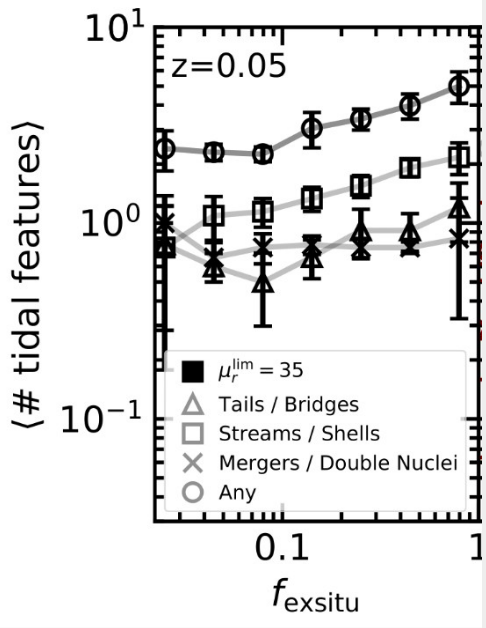


- At unlimited depth objects exhibit **complex and varied structures** in their extended light
- Almost all objects from $10^{9.5}M_{sun}$ to $10^{11.5}M_{sun}$ exhibit tidal features
- Even at low masses, most galaxies undergo frequent interactions, but not necessarily mergers (Martin+2021)
- Many MW mass galaxies are **expected to have visible tidal features at LSST 10 year depth**

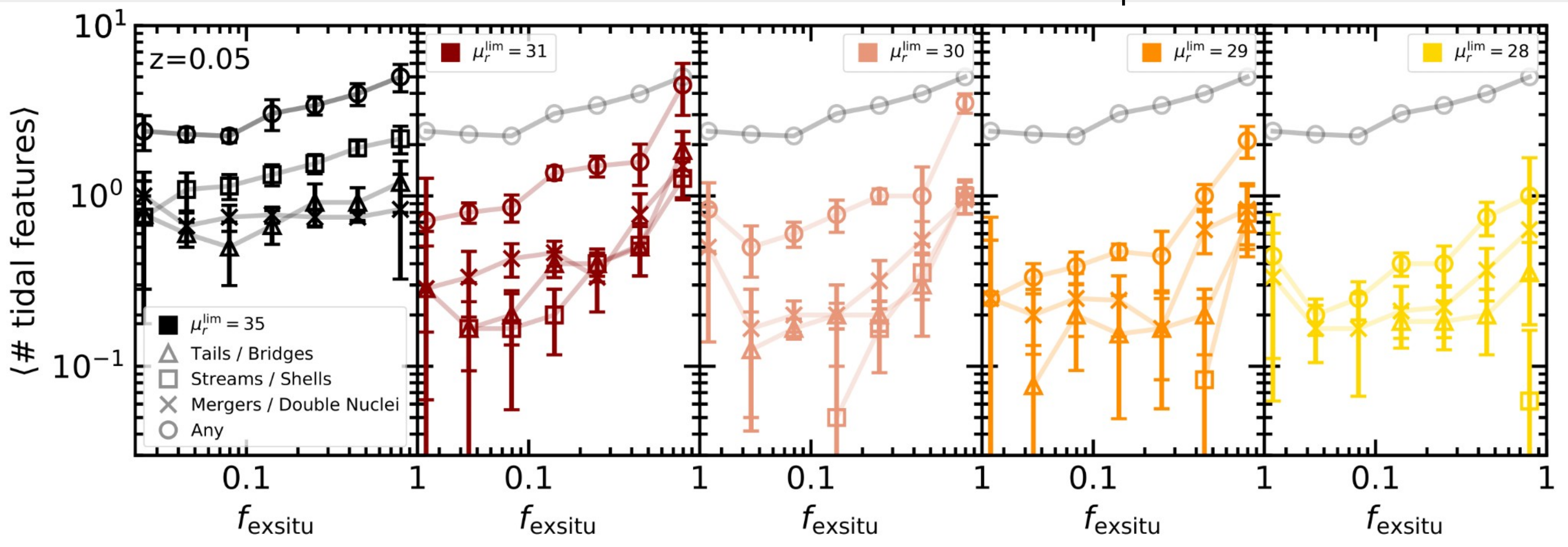
- Classifiers see more tidal features on average for higher ex-situ mass fractions
  - But different types of tidal feature exhibit different trends



Martin+2022, MNRAS, 513, 1, pp.1459-1487, arXiv:2203.07675

- Classifiers see more tidal features on average for higher ex-situ mass fractions
  - But different types of tidal feature exhibit different trends
  - Trends also evolve differently with limiting surface brightness
- Understanding detectability of tidal features around galaxies is complex since it depends on the class of tidal features present, the brightness of these tidal features and the imaging depth

deeper



Martin+2022, MNRAS, 513, 1, pp.1459-1487, arXiv:2203.07675

Visually classifying LSB features in the stellar halo

Uncertainty arises from visual differences in across projections of the same object AND disagreement between human classifiers

Deeper imaging helps, but in some cases <u>increasing depth</u> makes classification <u>more ambiguous</u>

- As depth improves, morphologies can become more complex, introducing uncertainty in precise characterisation

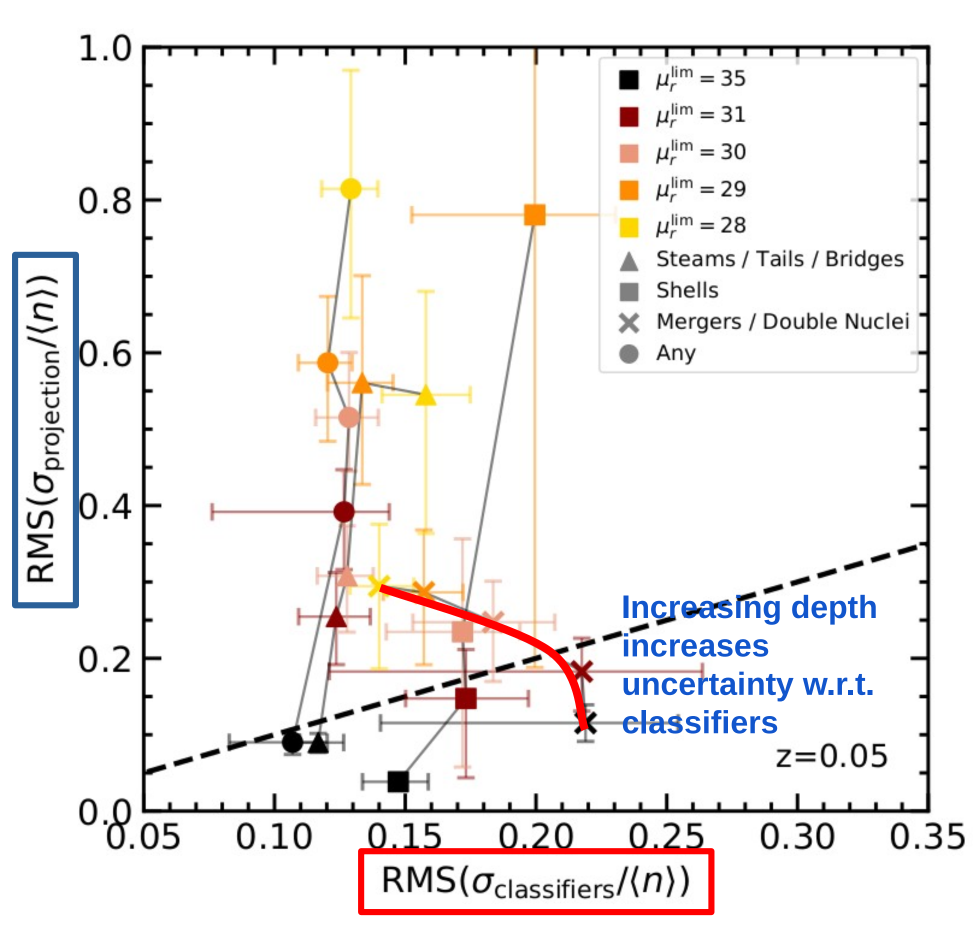
The <u>performance of human classifiers is poor</u>

- significant disagreement

- projection biases

- time consuming

- <u>clear need to automate the detection and measurement of tidal features</u>



New deep-wide datasets will be challenging to fully exploit due to:

- **Extreme data volumes:**
  - **Billions of objects, significant computational challenges**

- **Costly data processing:**
  - **Existing data processing methodologies are intractable**
  - **New methods needed for identifying and characterising sub-structures**

- **Unfamiliar / unexplored discovery space:**
  - **Poorly understood biases**
  - **Unknown underlying populations**
  - **No existing large datasets to test new techniques**

- **Issues with interpretation of data:**
  - **Robust comparison with theoretical predictions**
  - **Linking observed quantities to physical properties**

Without addressing the data challenges present in datasets like those produced by JWST, Euclid and Rubin, much of the potential of these facilities will be unrealized

Morphological classification challenges for LSST

LSST data volume will be unprecedented in astronomy
– Cadence of ~**3 days**

– ~ 30 galaxies / arcmin^2 (~**20 billion galaxies**/17 billion stars in total)

– Full reprocessing of survey data annually, but much more often for some applications

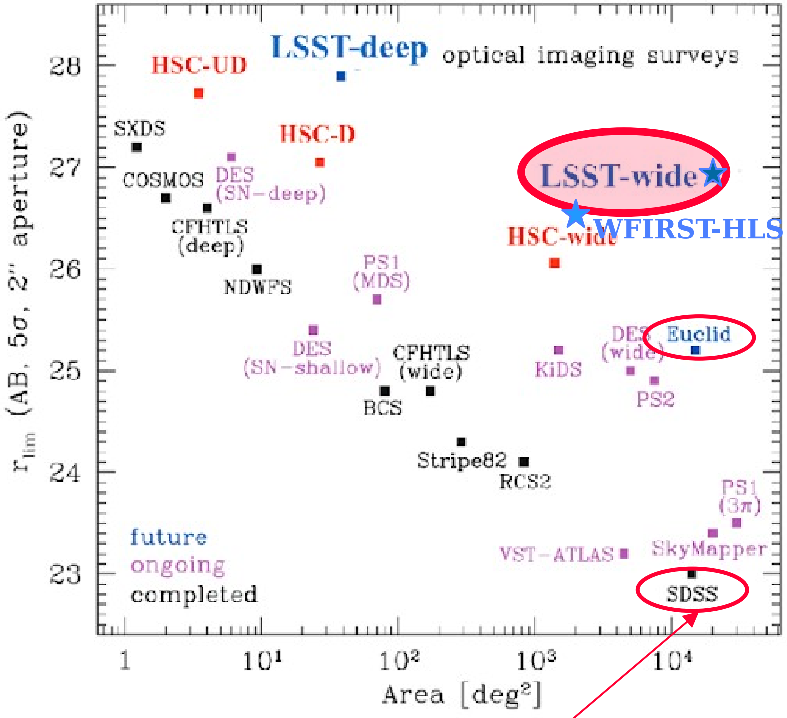
How do we classify all these objects?

– Rapidly changing datasets mean we may need to re-classify co-added data between data releases

– Repeated construction of **unbiased training sets** for high cadence (rapidly changing) data will be difficult

– The large area of LSST will allow the construction of samples of rare/faint types of object, but these object will not have robust training sets available

Other upcoming missions like Euclid and Roman represent similar challenges.



700,000 galaxies classified by volunteers over 4 years **(Lintott+2008)**

Solutions?

– Classifications based on raw image data using **citizen science** (e.g. galaxy zoo) and **machine learning** based techniques have produced high quality classifications in the past

– But as **data sets continue to grow**, human classification will become less and less viable

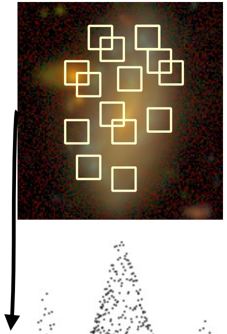
– Some hope that **citizen science combined with machine learning** e.g. **Beck et al. (2018)** can mitigate this, but very large data volumes will still be challenging

– Machine learning techniques are currently the only realistic solution, but high survey cadence and rapidly changing data mean **there are still challenges for supervised techniques**

– **Unsupervised** methods, which **do not require training sets, allow for discovery and do not introduce human bias** in the training stage represent a promising alternative

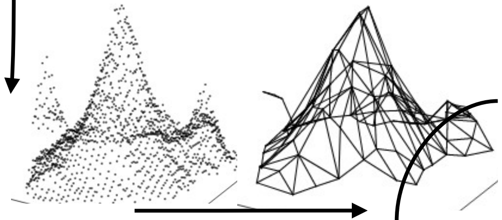
Application of an unsupervised technique

Hocking et al. (2018), Martin et al., (2020)



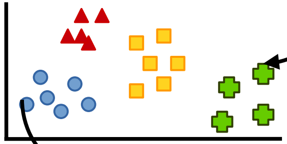
Convert the survey images into a data matrix

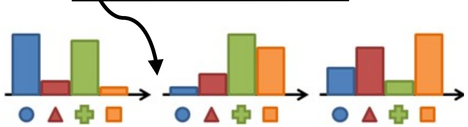
– Extract patches at each non-zero pixel in a multi-band image
– The radial power spectrum of a patch produces a rotationally invariant representation of the patch



Use Growing Neural Gas and Hierarchical Clustering to produce a condensed version of the original data set

– Using the output patches, iteratively fit the data using growing neural gas to produce a graph made up of nodes
– Each node in the graph represents a group of similar patches
– By applying hierarchical clustering, we can further reduce the number of groups by reducing them to similar 'types' of patches



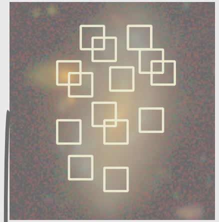


Create object sample vectors corresponding to patch 'types'

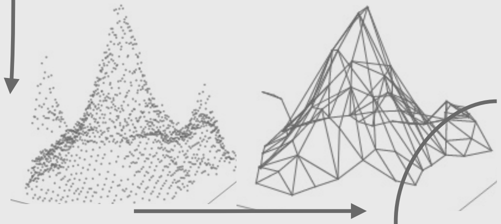
– Identify objects using connected component labelling (or existing segmentation map)
– Create a sample vector for each object, represented by a histogram of the different 'types' of patches they are formed from
– Sample vectors are weighted by tf*idf (term frequency-inverse document frequency)

Application of an unsupervised technique

Hocking et al. (2018), Martin et al., (2020)



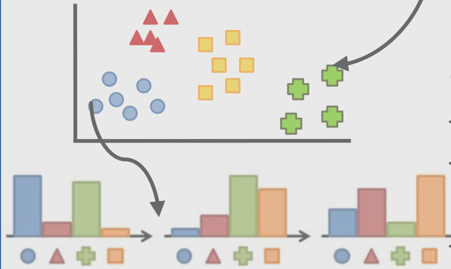
Convert the survey images into a data matrix
– Extract patche
– The radial pow
of the patch



Condensed version:

Use clustering techniques (**growing neural gas & hierarchical clustering**) to create a library of pixel ‘types’ based on colour, intensity and ‘texture’

Produce histogram descriptions (‘**feature vector**’) of objects that describe the frequency of each pixel type in that object



Create c
– Identify
– Create
‘types’ of
– Sample vectors are weighted by tf*idf (term frequency-inverse document frequency)

Application of an unsupervised technique

– Alternative feature extraction approaches may also be effective e.g. using neural networks to select features instead of engineering the features

– The modeling and clustering steps only need to be performed once for a **representative sample of the data (a few thousand objects)**.

– Using the same model we can then apply the algorithm to unseen data.

– **~30- 40 milliseconds per pixel** using a single thread of execution for the first pass modelling / classification step.

– Once the first pass is completed only **1.5 milliseconds per pixel for classification** of subsequent similar data (e.g. more patches of the same survey).

– **SDSS in a few days** on a HPC cluster. **Not yet optimised…** Work currently being undertaken by Ilin Lazar to optimize for LSST.

Application of an unsupervised technique

Using each object’s sample vector we can:

a) **Automatically group objects by using an additional clustering step**

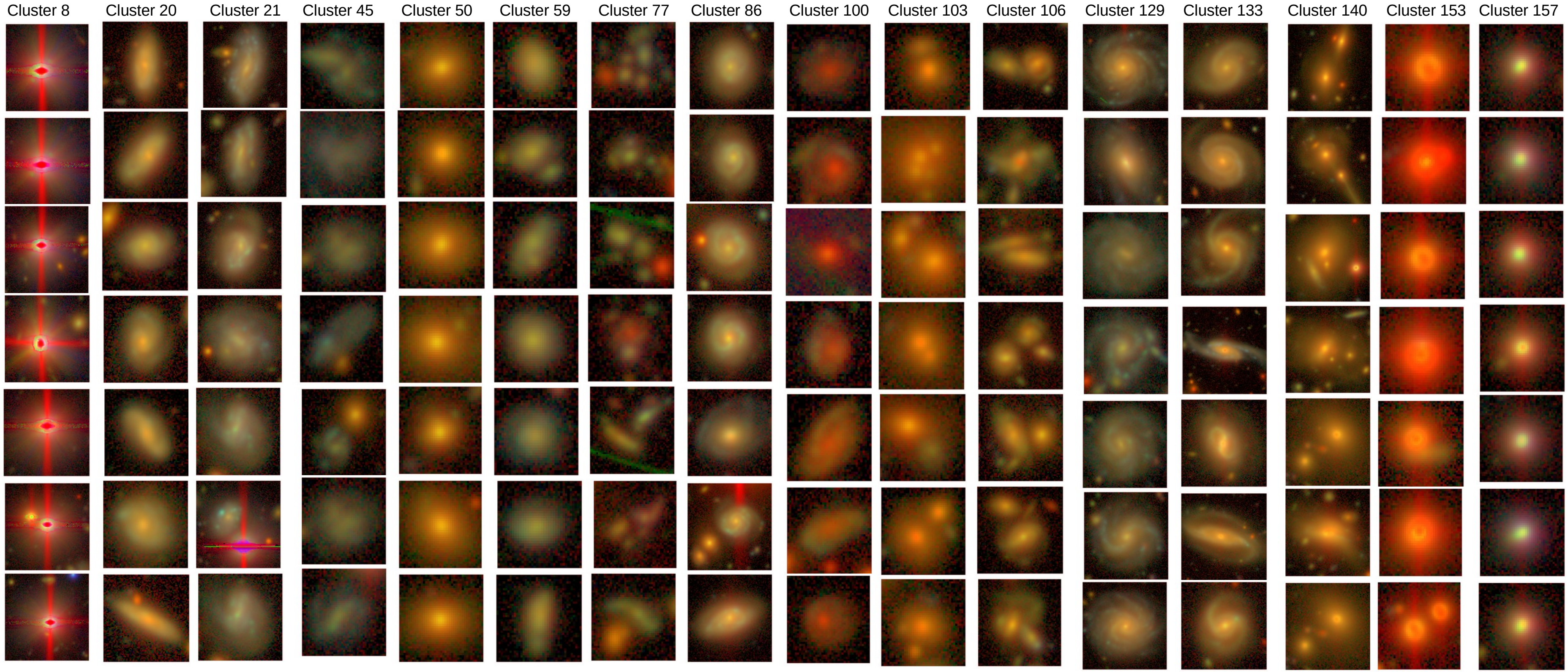
– Can be applied to the the whole set of object sample vectors
– Identify **arbitrary groups** of objects with similar feature vectors
– Groups of like objects have **no semantic labels**

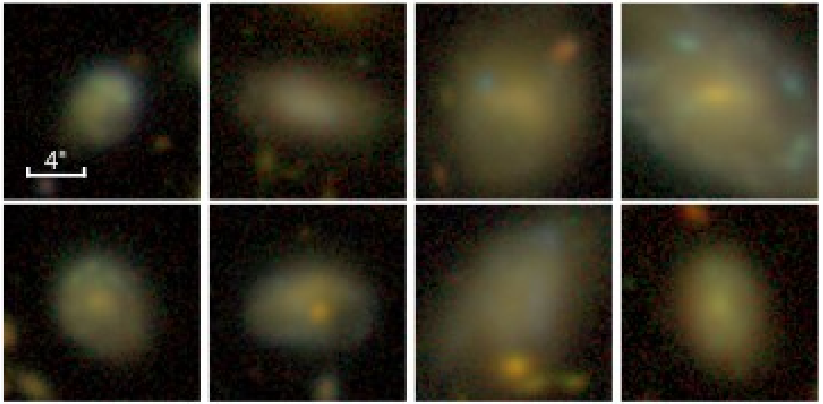
b) **Discover objects similar to a given target object**

– Find the objects whose sample vectors are closest to the target sample vector
– Use some distance measure (Pearson correlation coefficient, Cosine distance, etc)

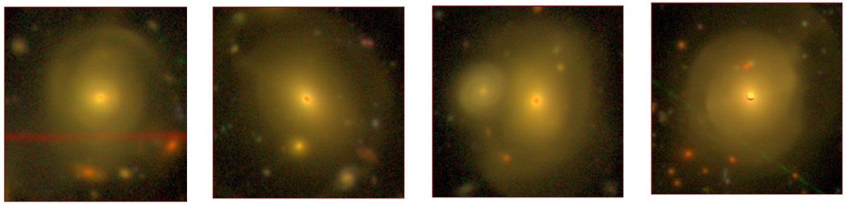
Automatic classification of HSC-SSP *ultra deep DR1* data (LSST-like)

Martin et al. (2020)

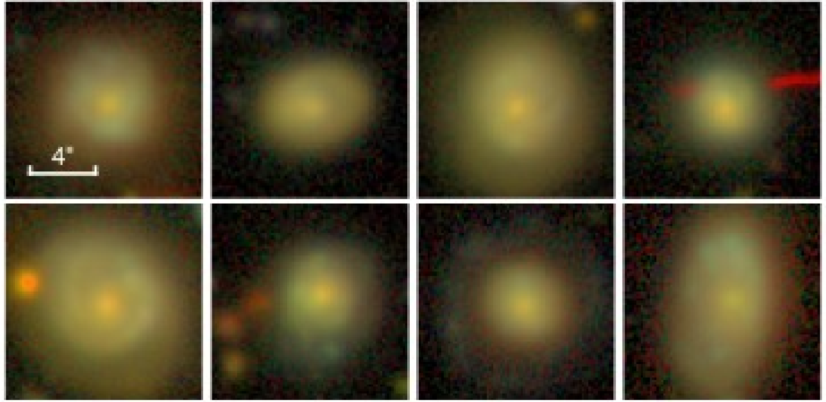




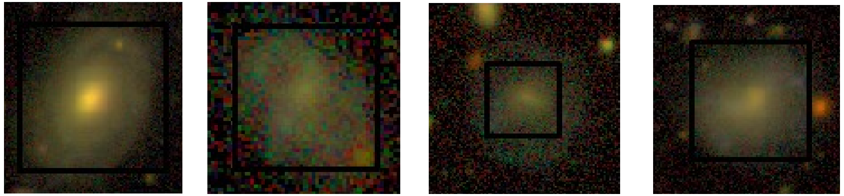
Clumpy discs



Shells



Rings / accretion events

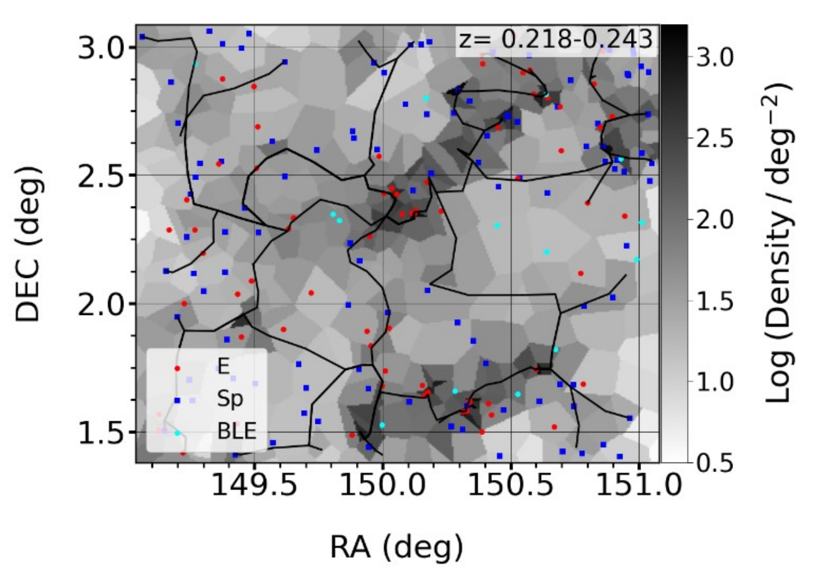


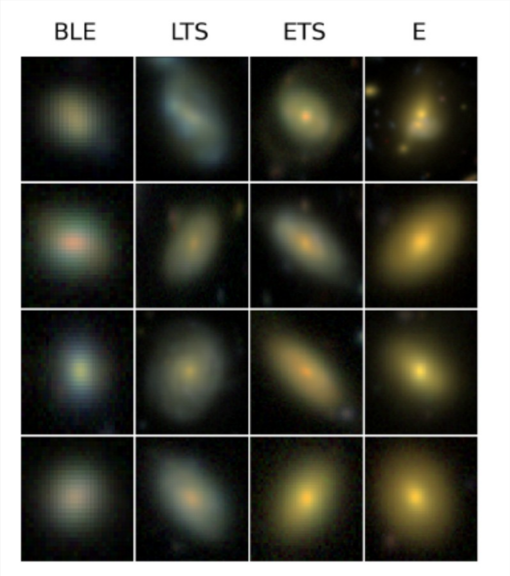
LSB discs

Some more examples of individual clusters featuring rare/specific types of object

(i.e. groups of object with similar feature vectors)

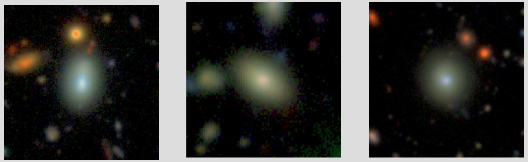
Lazar+2023, MNRAS 520, 2, pp.2109-2120



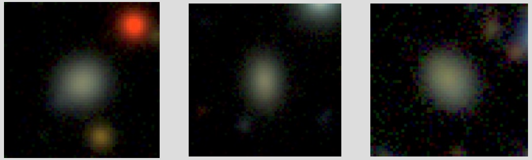


Already used in Cosmos to find relaxed blue elliptical galaxies and identify likely formation mechanisms

- They lie in less dense environments, specifically far from large-scale filaments.
    - their formation is likely driven by secular gas accretion away from competition from more massive galaxies



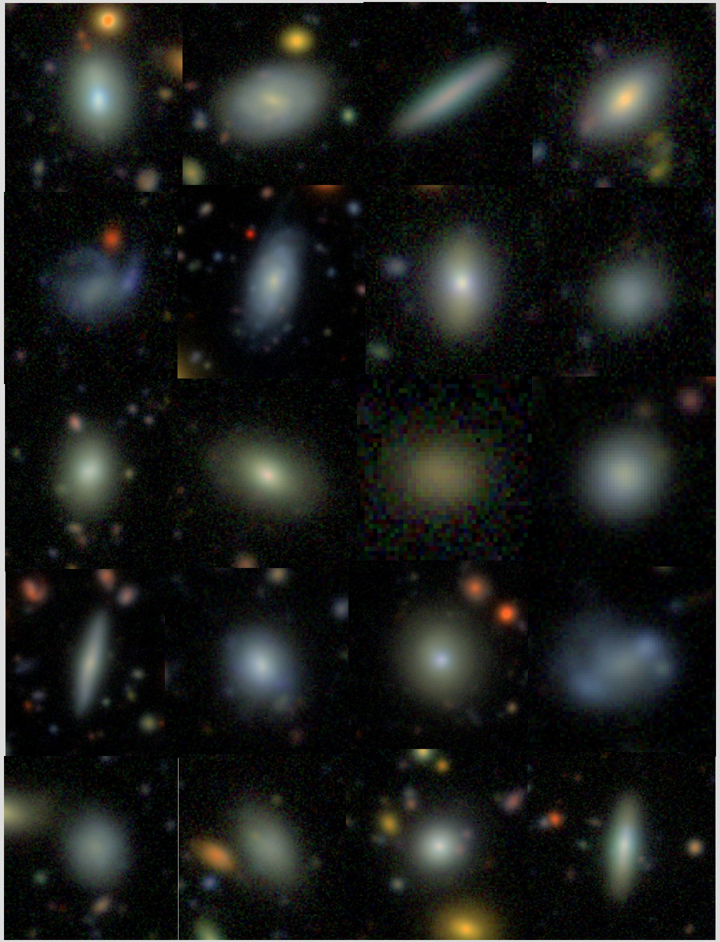
ETG



Pancake

Additionally, we identify galaxies with ‘pancake’ or ‘lens’ type morphology (**Lazar+ in prep**)

- a class unique to the low-mass regime
- may be formed by feedback or tidal perturbations
- useful for constraining feedback implemented in galaxy formation models



Application of an unsupervised technique

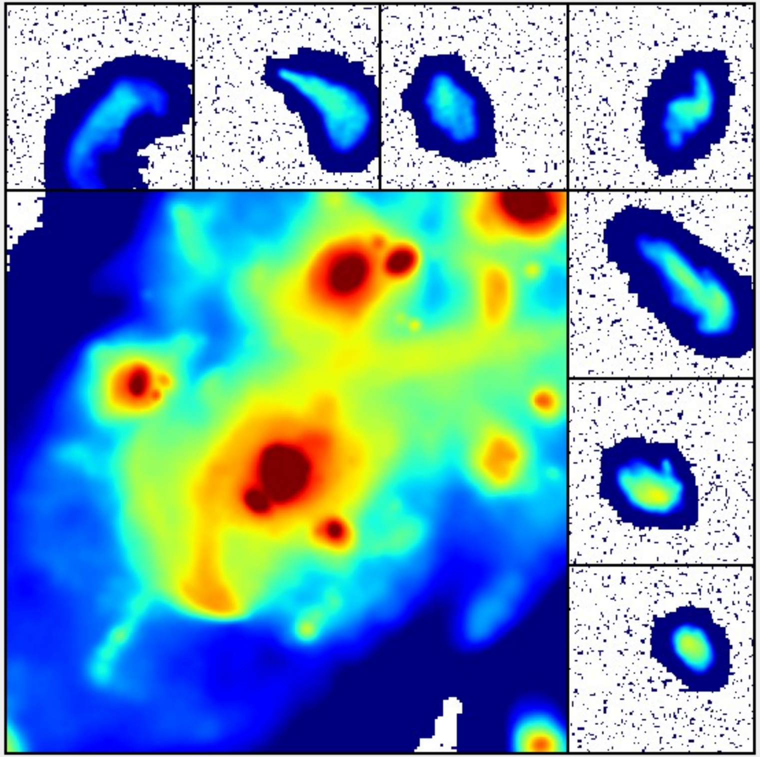
Ultimately, we can use techniques like this to identify sub-components within galaxies which are represented by different parts of the galaxy feature vector.

We can then use this to link observed and synthetic examples of different galaxy substructures by comparing their visual similarity based on the distance between their feature vectors.

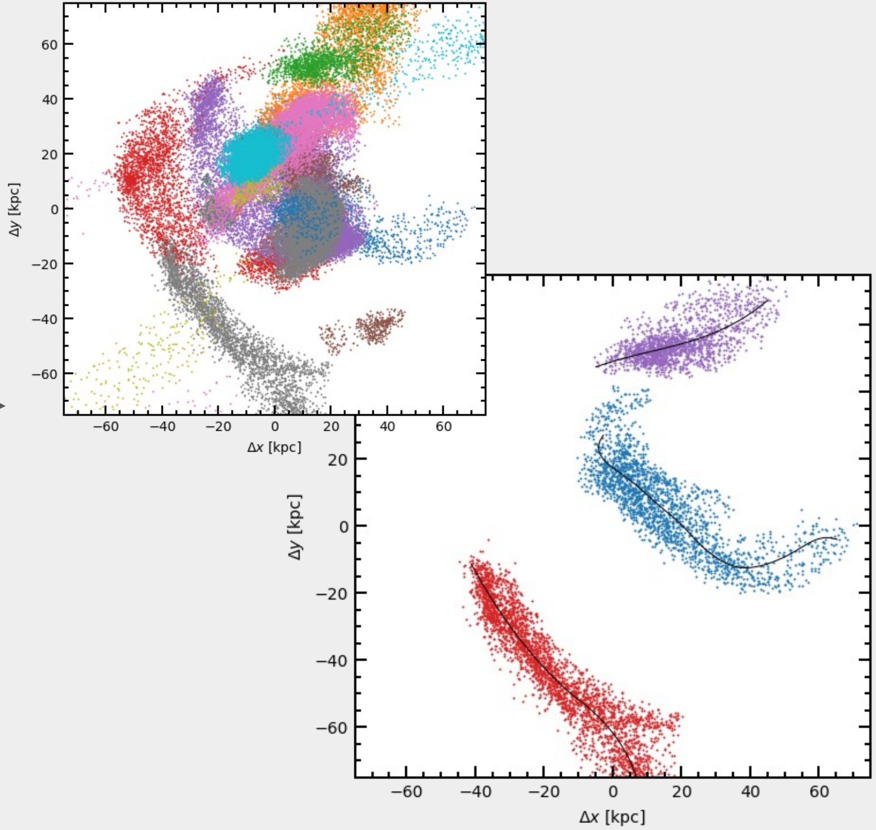
MNRAS, 513, 1, pp.1459-1487, arXiv:2203.07675

Future work: automatic identification and measurement of tidal features

6-D Kinematically coherent features identified using clustering hierarchical density-based clustering (HDBSCAN, **McInnes+2017**)



Measure properties of individual tidal features along the medial spine of each tidal feature



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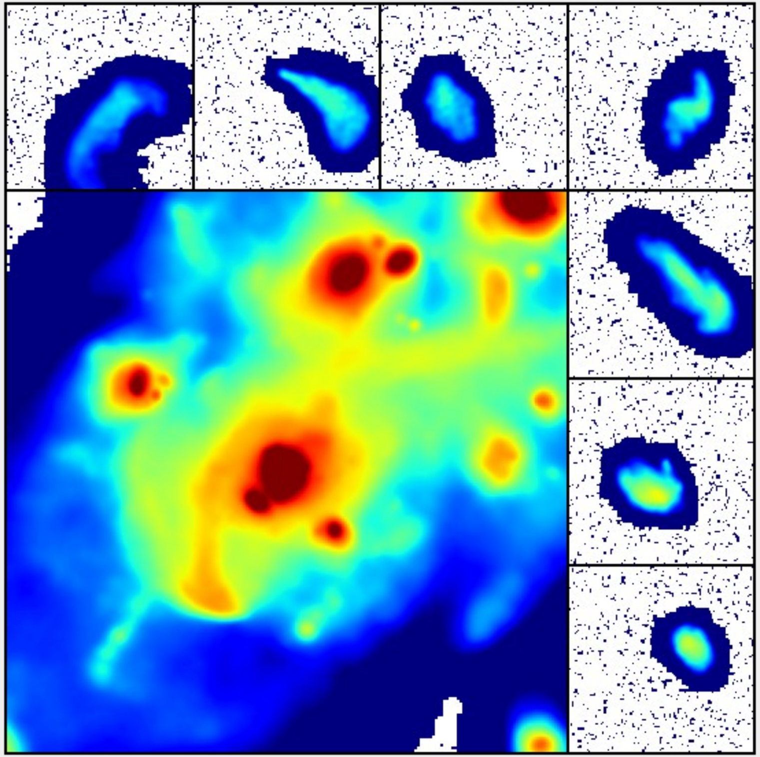

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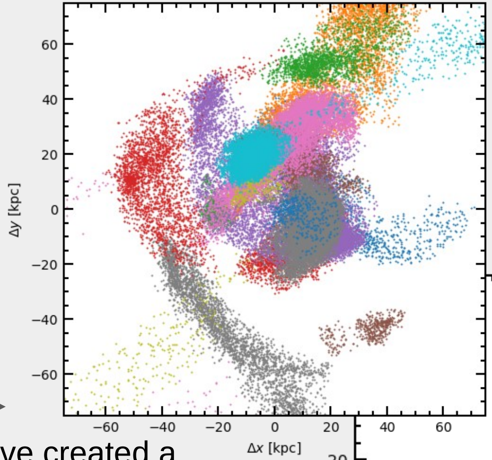

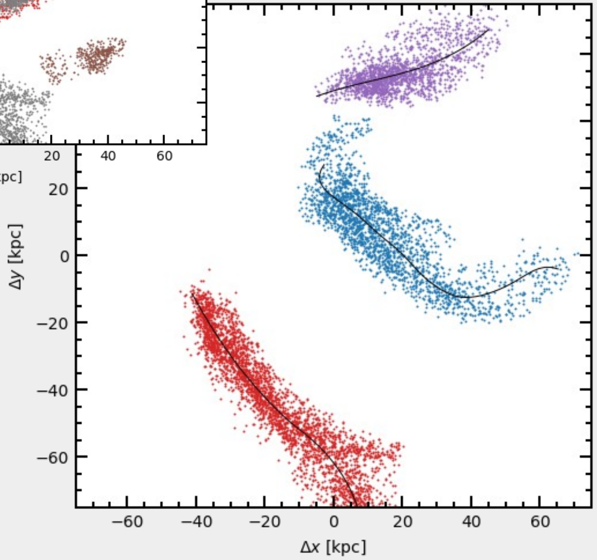

Once we have created a library of synthetic tidal features viewed in many different projections, we can compare these projected measurements with those of observed features in order to recover de-projected measurements as well as information about likely progenitors.

Addressing the challenges of new datasets with:

(1) Synthetic datasets / observations
- Inform development of tools / techniques and quantify biases and recovered properties under realistic viewing conditions

(2) Efficient unsupervised machine learning techniques
- Characterise and segment tidal features in an unbiased manner

(3) Tools to effectively interpret tidal features
- Connect the synthetic properties of sub-structures with observed counterparts through comparison with like-for-like comparison of measurements with observed and synthetic features
- Recover robust assembly histories for observed galaxies.

(4) Connection to the cosmic environment
- Develop tools to compare galaxy assembly histories and properties in the context of the large-scale filamentary structure of the Universe

Conclusions and future plans

Conclusions

- After its 10 year survey, LSST will have sufficient depth to resolve a significant fraction of the flux found in tidal substructures of MW galaxy stellar haloes
- Around 75% of flux lies in these denser tidal features rather than more diffuse tidal debris which lie beyond the surface brightness limits accessible to LSST
- At sufficient depth, almost 100% of galaxies ($M_*/M_\odot<10^{9.5}$) possess tidal features
- Surface brightness limits, galaxy orientation, redshift, etc. have a clear effect on the ability of expert classifiers to visually identify and characterise tidal features
- Concurrence between classifiers generally improves with deeper imaging but morphologies can become more complex, introducing uncertainty in precise characterisation
- ML techniques, in conjunction with synthetic observations provide an avenue to efficiently and robustly identify and characterise tidal features and make physical inferences including recover assembly histories

Future work

- Directly compare automated measurements of simulated tidal features with human classifications
- Expected frequency and distribution of tidal features as a function of surface brightness
- Expected distribution of tidal feature properties – length, curvature, colour etc.

MNRAS, 513, 1, pp.1459-1487, arXiv:2203.07675

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