

Simulating intrinsic alignments:

from hydrodynamical simulations to deep learning generative models

Rachel Mandelbaum, 12/2022

Context for this talk

I've been fortunate to have collaborated with many participants in this workshop, and have tried to make my talk complementary and give them chances to present their own work!

Will present on topics related to galaxy shape alignments and IA simulations:

1. Recent work in hydrodynamical simulations
 - a. IA versus morphology and color
 - b. Constraints on the IA model
2. Perspective on hydro simulations: how can/can't we use them for this purpose?
3. Beyond hydro: emulation of alignments using deep learning

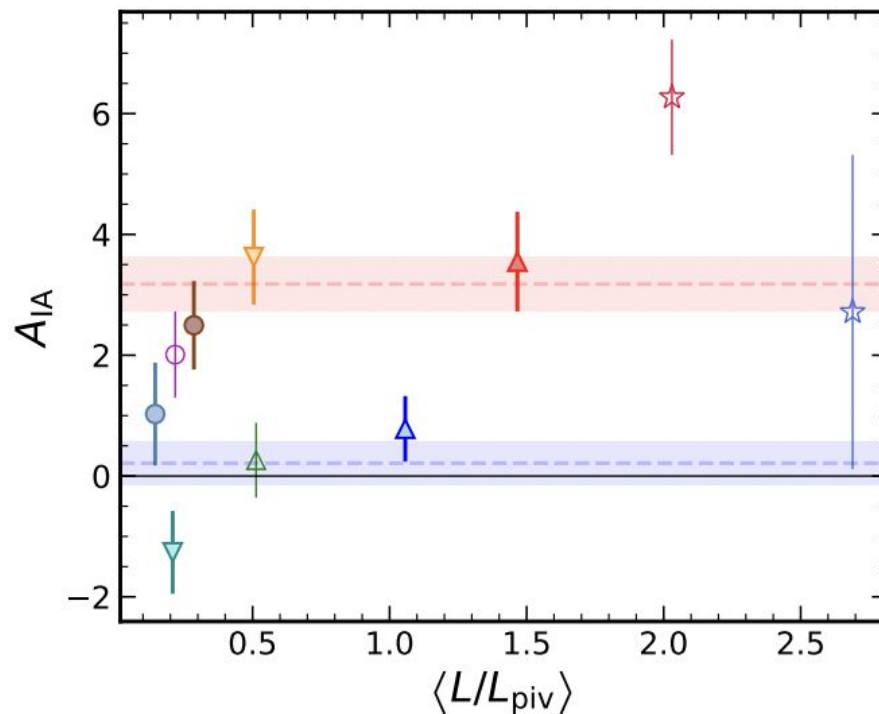
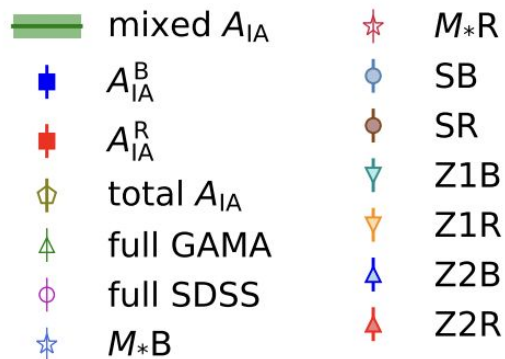
Have assumed background from some other talks.

Recent work in hydrodynamical simulations

Observations clearly indicate color bimodality in IA strength

Red vs. blue bimodality was detected early (~ 15 years ago) but has become increasingly evident.

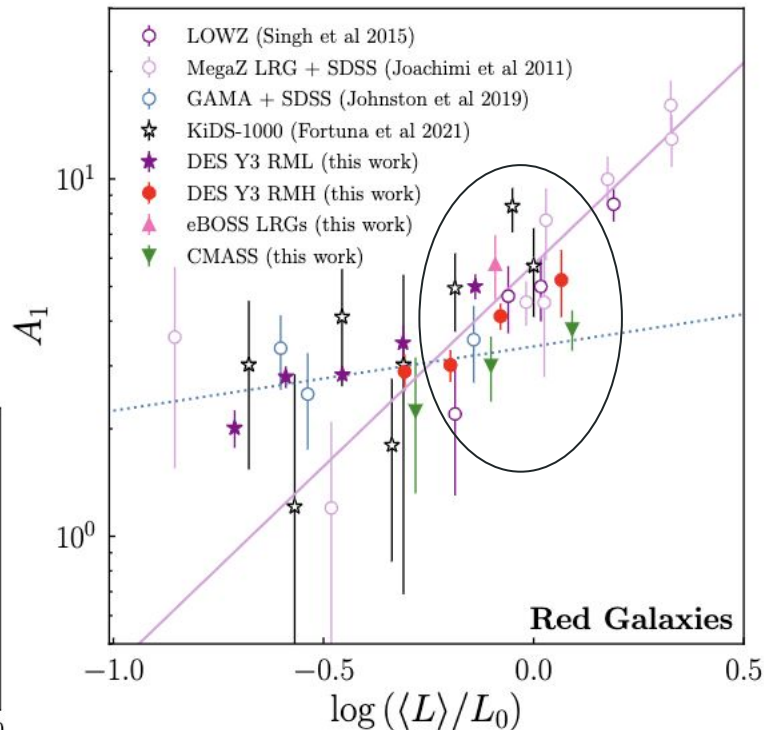
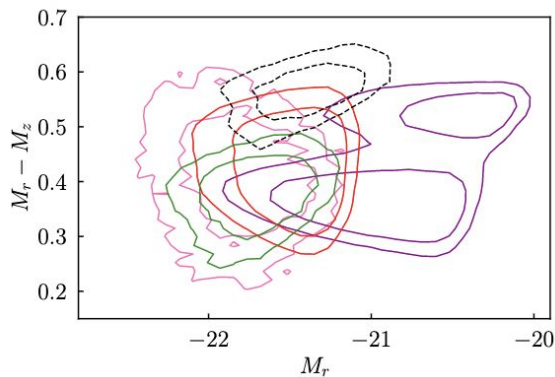
Image credit: Johnston+ (2019)



Even within the red sequence, there are signs of a non-monolithic population

Samuroff+22 (in prep): even for red populations, the trend in IA amplitude is inconsistent across populations with different rest-frame colors

- LOWZ
- eBOSS LRGs
- eBOSS ELGs
- redMaGiC low- z
- redMaGiC high- z
- CMASS



There are physical reasons to connect this with morphology and kinematics

- Disk galaxies have a special direction, the angular momentum vector, which could give rise to tidal torquing effects from the environment
 - This gives shape alignments that are quadratic in the tidal field
- For pressure-supported galaxies, the major axis direction is the main direction that could respond to large-scale tidal fields
 - This gives shape alignments that are linear in the tidal field

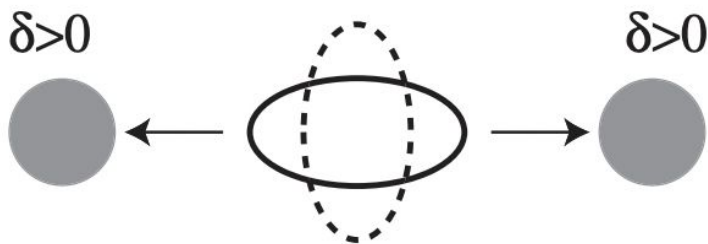


Image credit:
Hirata & Seljak (2004)

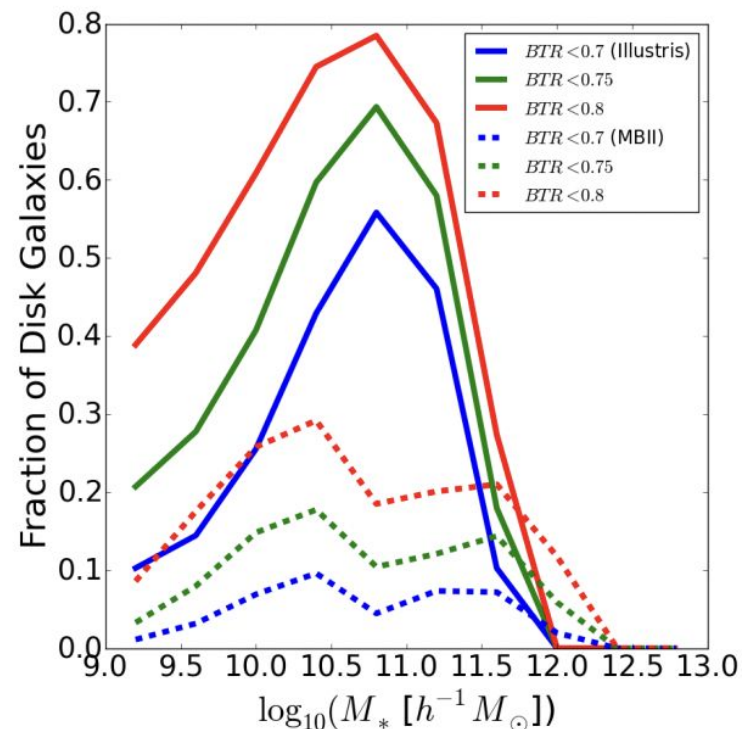
Simulations and morphological classification: challenges

Hydrodynamical simulations seem like a great testbed for this physics, but morphological classification is unexpectedly challenging!

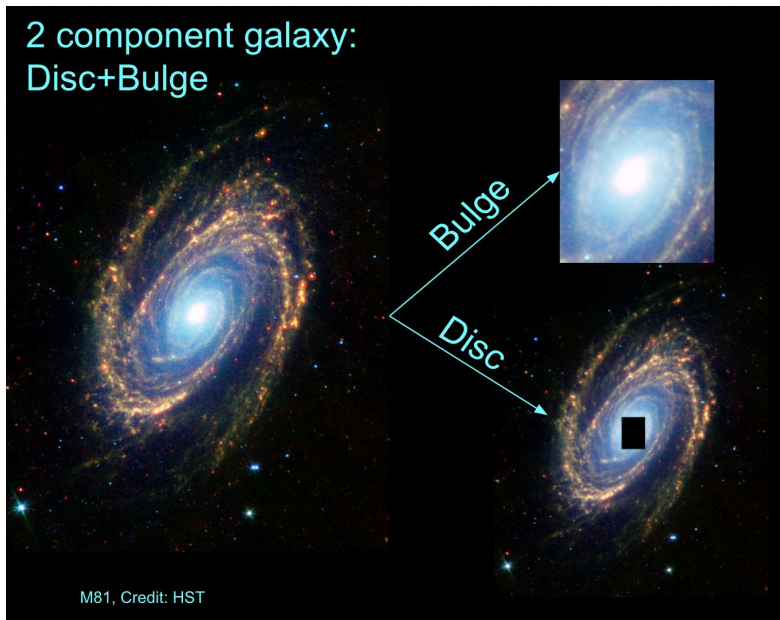
Image credit: Tenneti+16

Two different simulations give very different disc fractions. Possible reasons:

- Different subgrid physics results in different disc fractions.
- Morphological classifiers fail to cope with different disc thicknesses.



Advances in morphological classification will enable IA-morphology studies



We want to ...

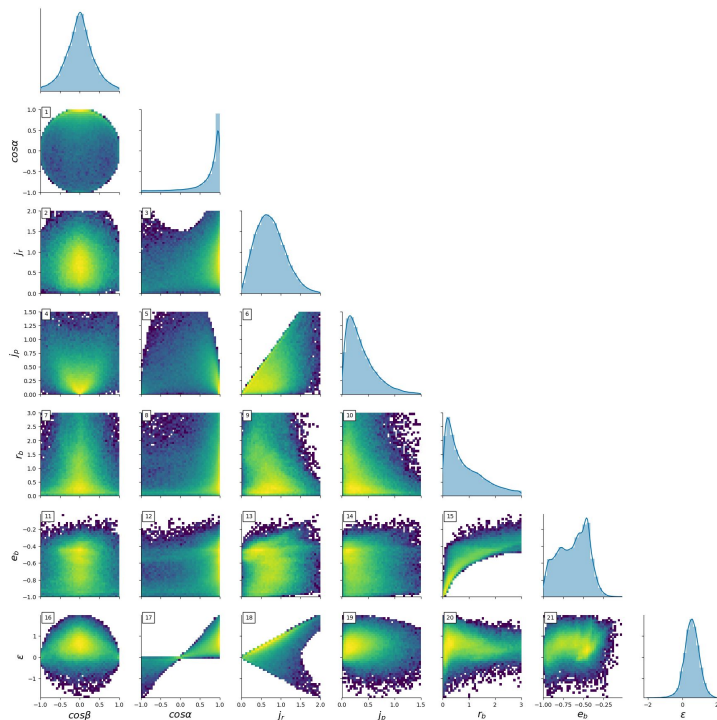
- Identify disc- vs bulge-dominated galaxies
- Associate particles with disc or bulge, so as to study their behaviors (e.g., intrinsic alignments) separately

This section covers the results in Jagvaral et al. (2022a, b):

<https://ui.adsabs.harvard.edu/abs/2022MNRAS.514.1021J/abstract>

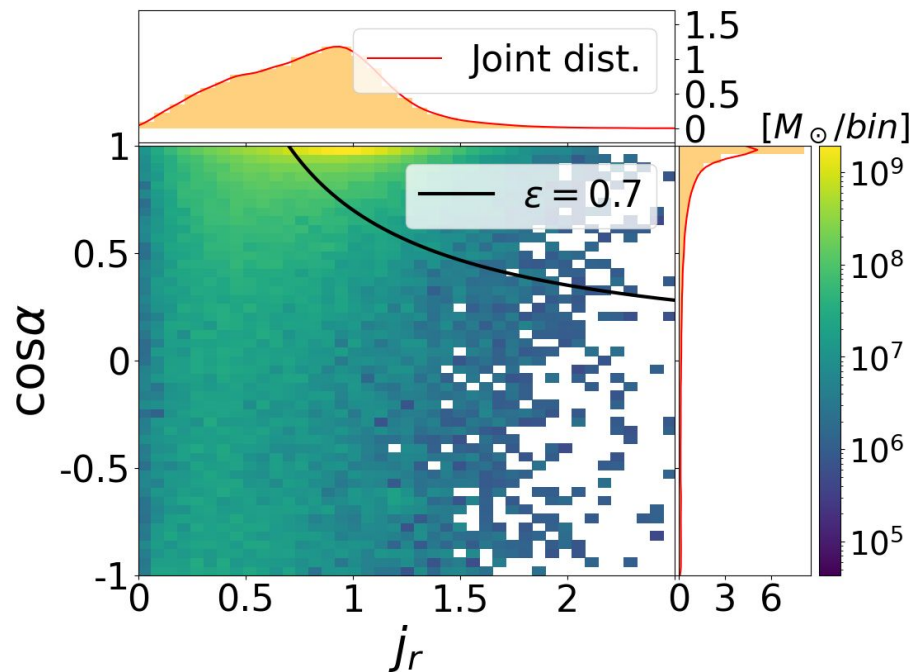
<https://ui.adsabs.harvard.edu/abs/2022MNRAS.509.1764J/abstract>

Advances in morphological classification will enable IA-morphology studies



There are many possible dynamical parameters that can be calculated for individual star particles, and used to say something about dynamics.

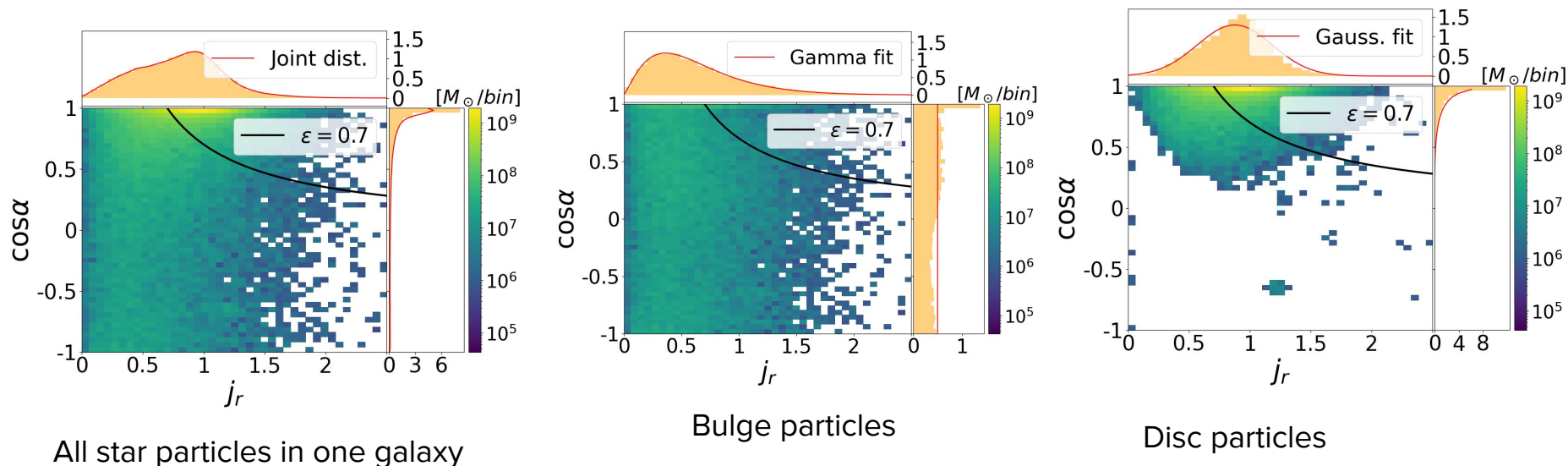
Advances in morphological classification will enable IA-morphology studies



Vertical axis: cosine of angle between galaxy angular momentum and star angular momentum

Horizontal axis: star angular momentum divided by the angular momentum for a circular orbit at that radius

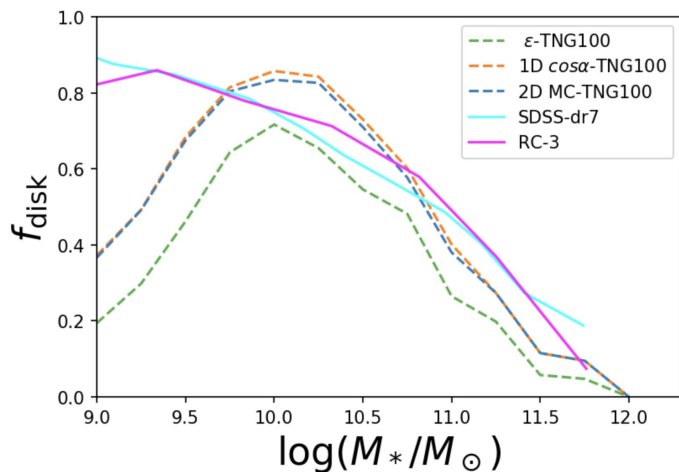
Advances in morphological classification will enable IA-morphology studies



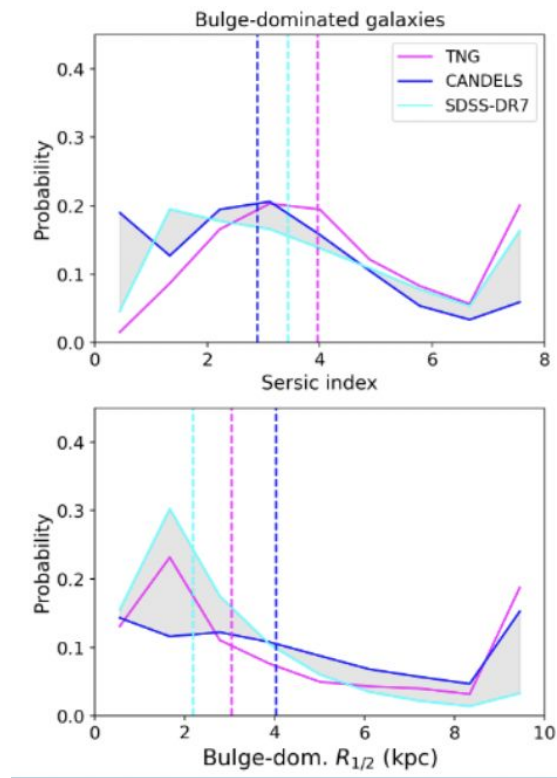
The method can efficiently identify star particles in the bulge/disc, and is more reliable than previous methods (e.g., circularity parameter)

Morphological classification: application

This new morphological classifier can identify bulge/disc particles, and allow us to measure bulge/disc properties for comparison with data

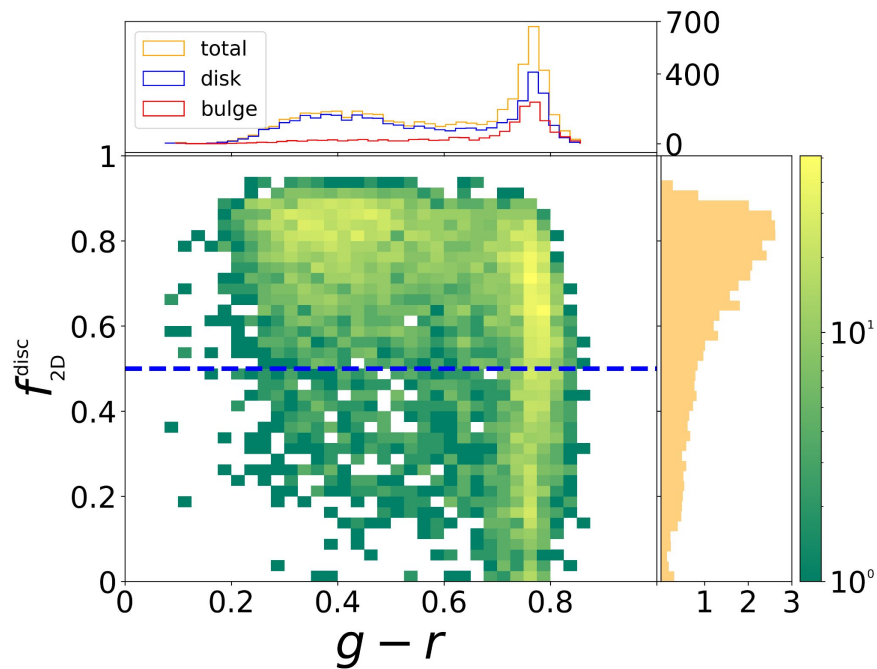
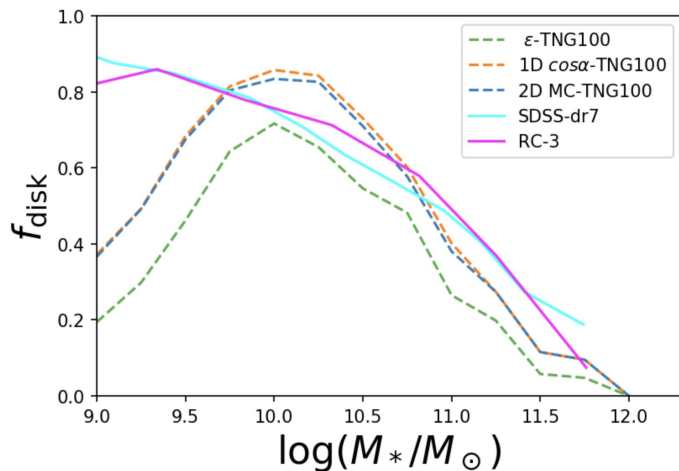


Favorable comparisons:
Disc fraction,
bulge properties



Morphological classification: application

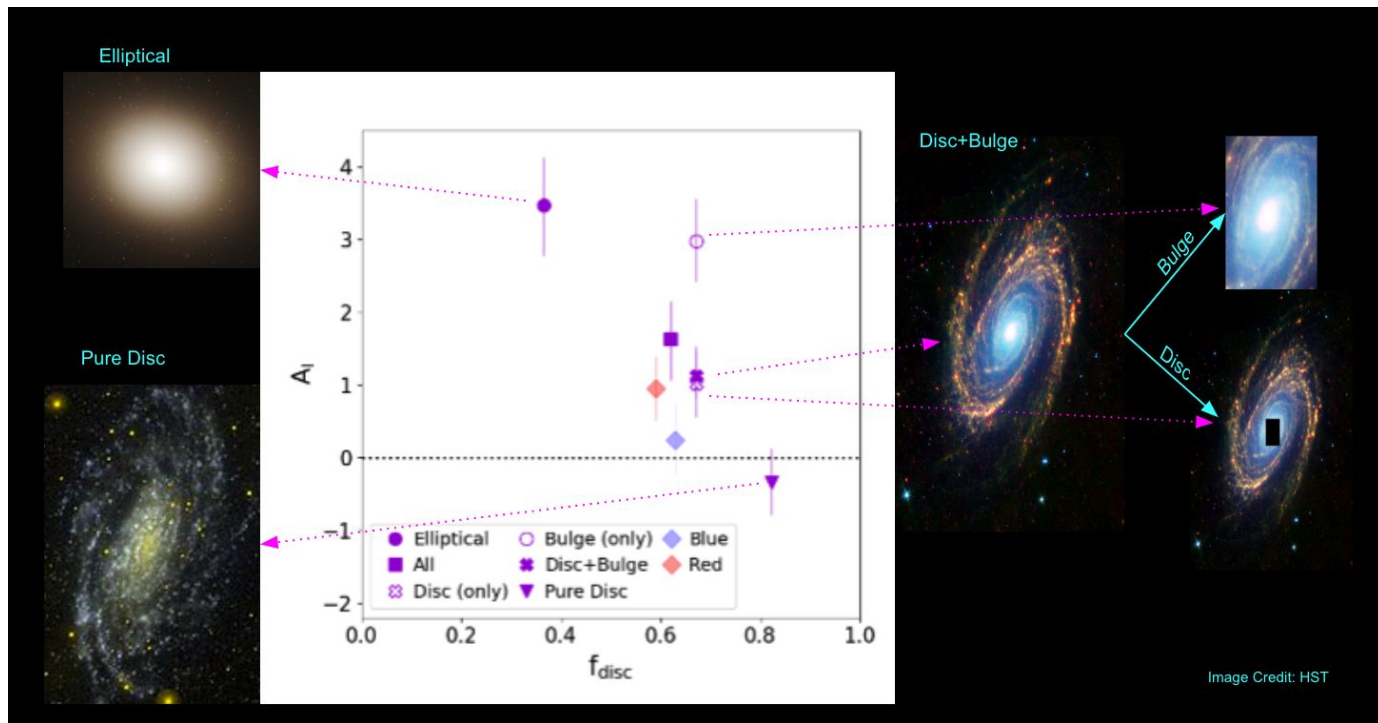
This new morphological classifier can identify bulge/disc particles, and allow us to measure bulge/disc properties for comparison with data



But the simulation has too many red discs?

IA results from morphological classification

While controlling for galaxy mass, we find a strong trend with morphology – even stronger than the trend with color.

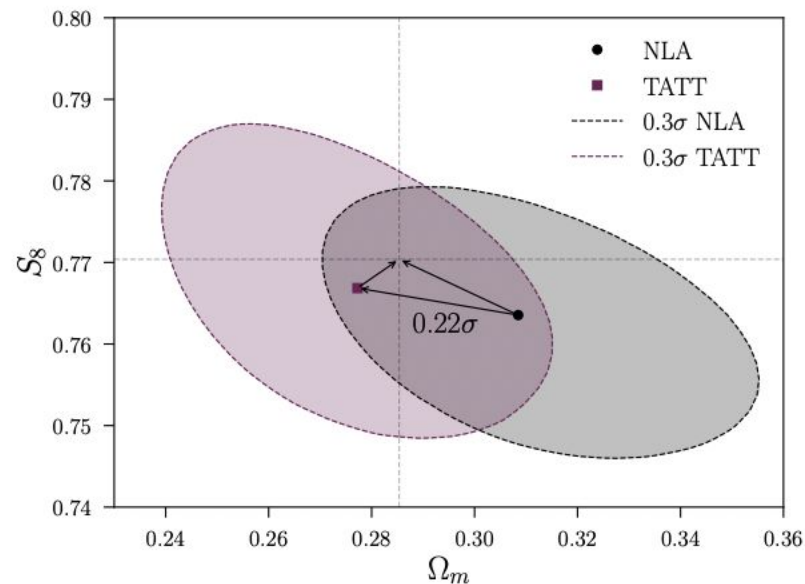


Morphology conclusions and outlook

- Improved morphological classification enables studies of IA as a function of dynamics, to better understand IA models and their dependence on the galaxy population.
- Can extend this to understand the evolution of alignments due to mergers and other factors affecting the galaxy population

The importance of IA model determination

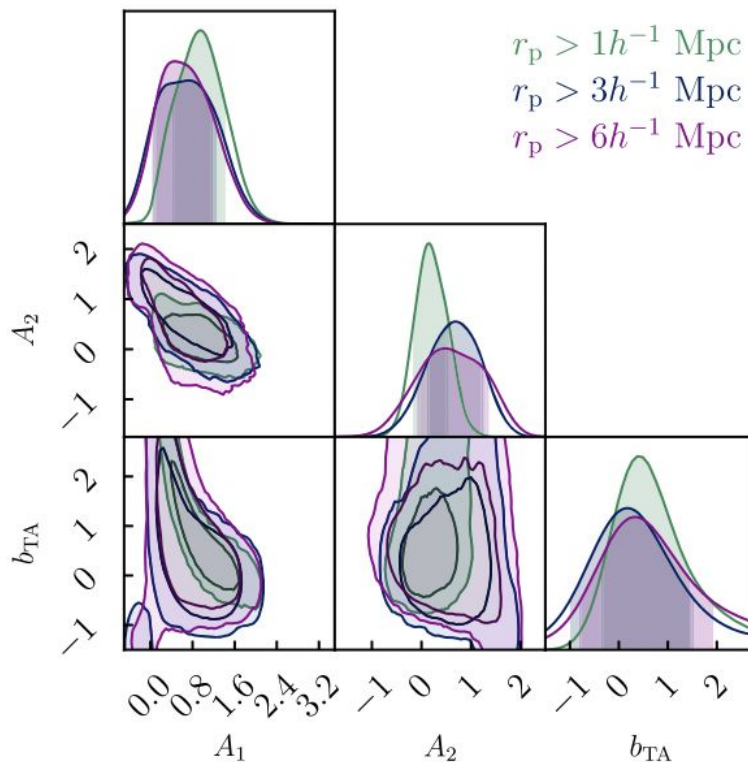
- In a cosmological analysis, if our model (including the IA model) is misspecified, then cosmological parameters may be biased.
 - Image credit: Campos+2022
- But having a too-complex model can result in other issues with inflated uncertainties, projection effects.



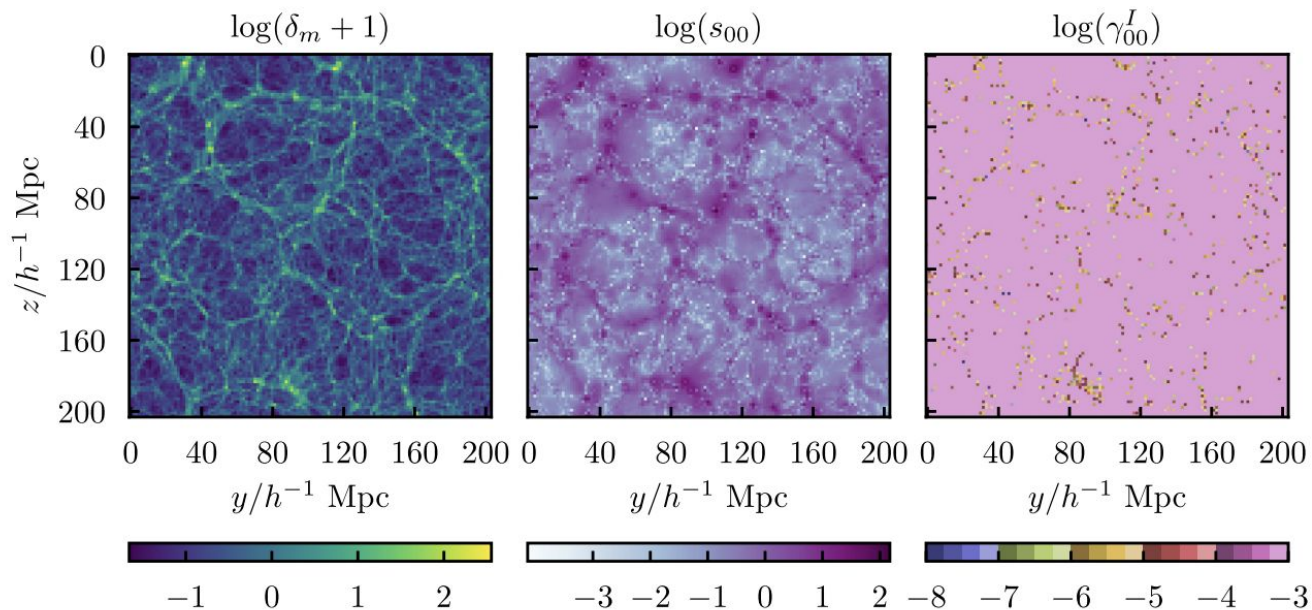
Simulation investigations into the IA model

- We'd like an empirical approach to model selection if we don't know the true IA model (Campos+22)
- Perhaps direct measurements and simulations can tell us the true IA model to the needed precision?

Samuroff+2022: no evidence for nonzero TATT parameters in Illustris TNG, when fitting down to 1 Mpc/h separations



However, simulations have more information we can use



Instead of IA two-point correlations, we can directly correlate with tidal fields!

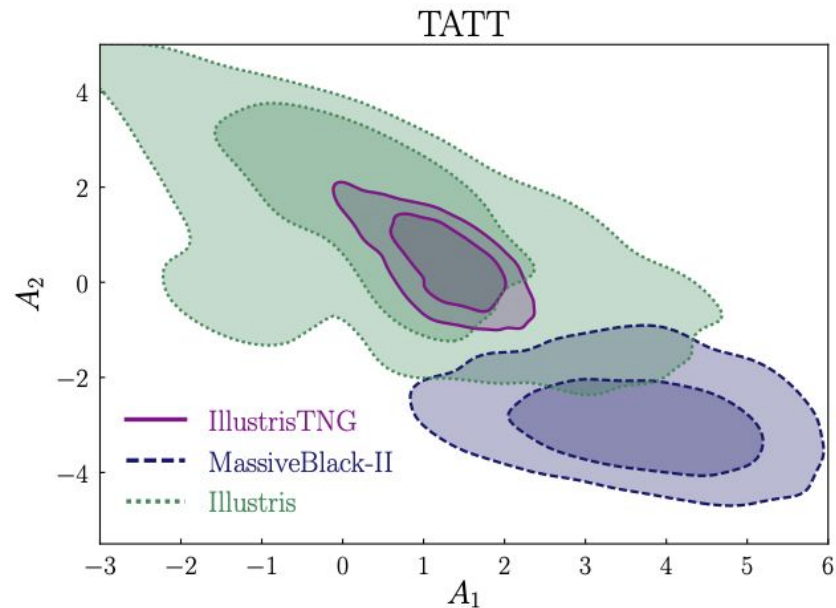
Zjupa+2022 has carried out local IA estimates using this approach

This approach is in its infancy and deserves further exploration.

The limitations of hydrodynamical simulations for IA studies

The limitations of hydrodynamical simulations

- The realized galaxy populations depend on subgrid physics
 - We don't care about differences like rescaling of IA amplitudes
 - We do care about less trivial differences in the physics of the population
- The simulations are very expensive: cannot generate the large-volume mock catalogs we want for testing WL analysis methods for upcoming surveys



Samuroff+22: signs of TATT in MassiveBlack-II?

Philosophy

Use them, but don't blindly trust!

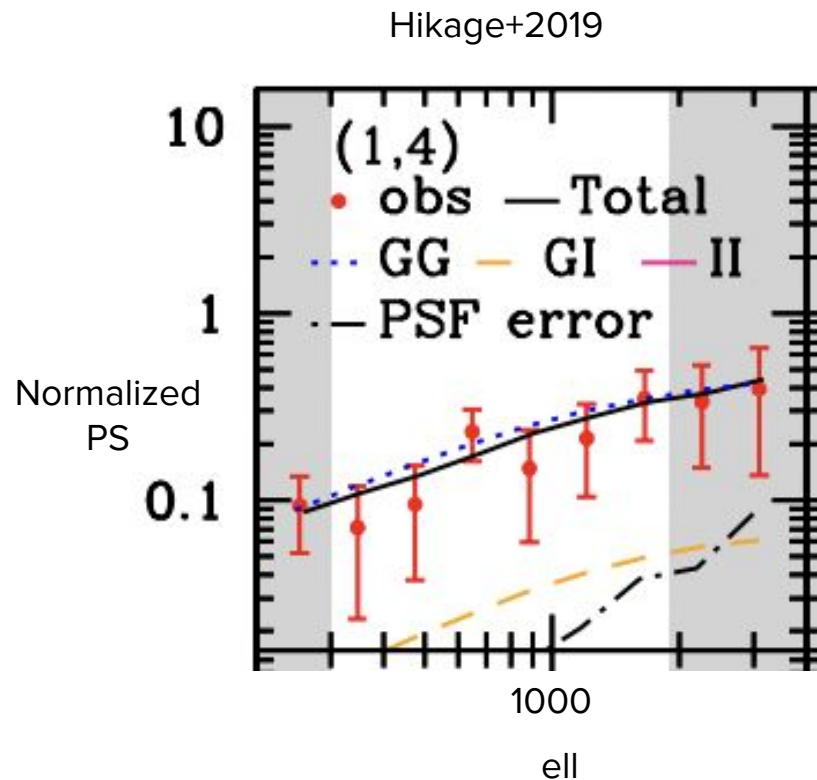
- Can adopt increasingly realistic simulations and safely disregard those that fail in multiple ways to describe the galaxy populations of interest.
- Can use multiple simulations to check how sensitive predictions are to subgrid physics.
- Can make testable predictions in these limited volumes, for comparison with direct measurement. It's OK if these are for samples that aren't used for cosmic shear – it still inspires confidence in the physics.

Deep learning emulation of IA

Testing IA mitigation methods

IA signals have a strong degeneracy with cosmological lensing. Testing modeling/mitigation methods using mock catalogs is important!

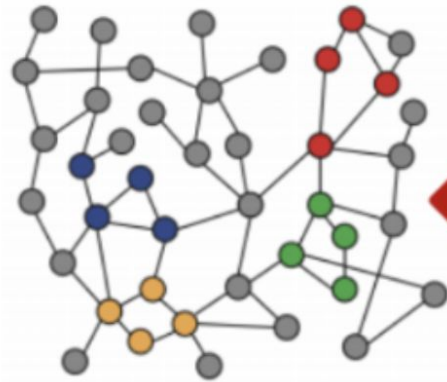
- If they have emulated alignments with the same IA model used for mitigation → GIGO!
- Mocks should ideally include degrees of freedom we cannot easily predict in reality.
- When using a parametric modeling scheme, should have non-parametric mocks.



Deep learning infusion methods

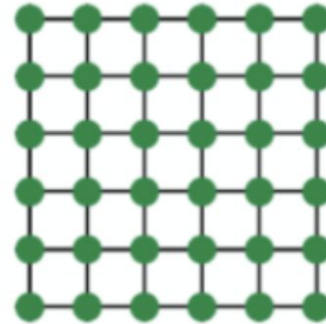
- Deep learning provides a non-parametric approach to infusion
- With varying training samples and constraints, multiple different realizations can be produced.
- They are an important part of the toolkit for future surveys, alongside parametric mocks (e.g., Harnois-Deraps 2022) and other physics-based approaches.

Graph neural networks: the right tool for galaxy distributions and the cosmic web



Networks

VS.



Images



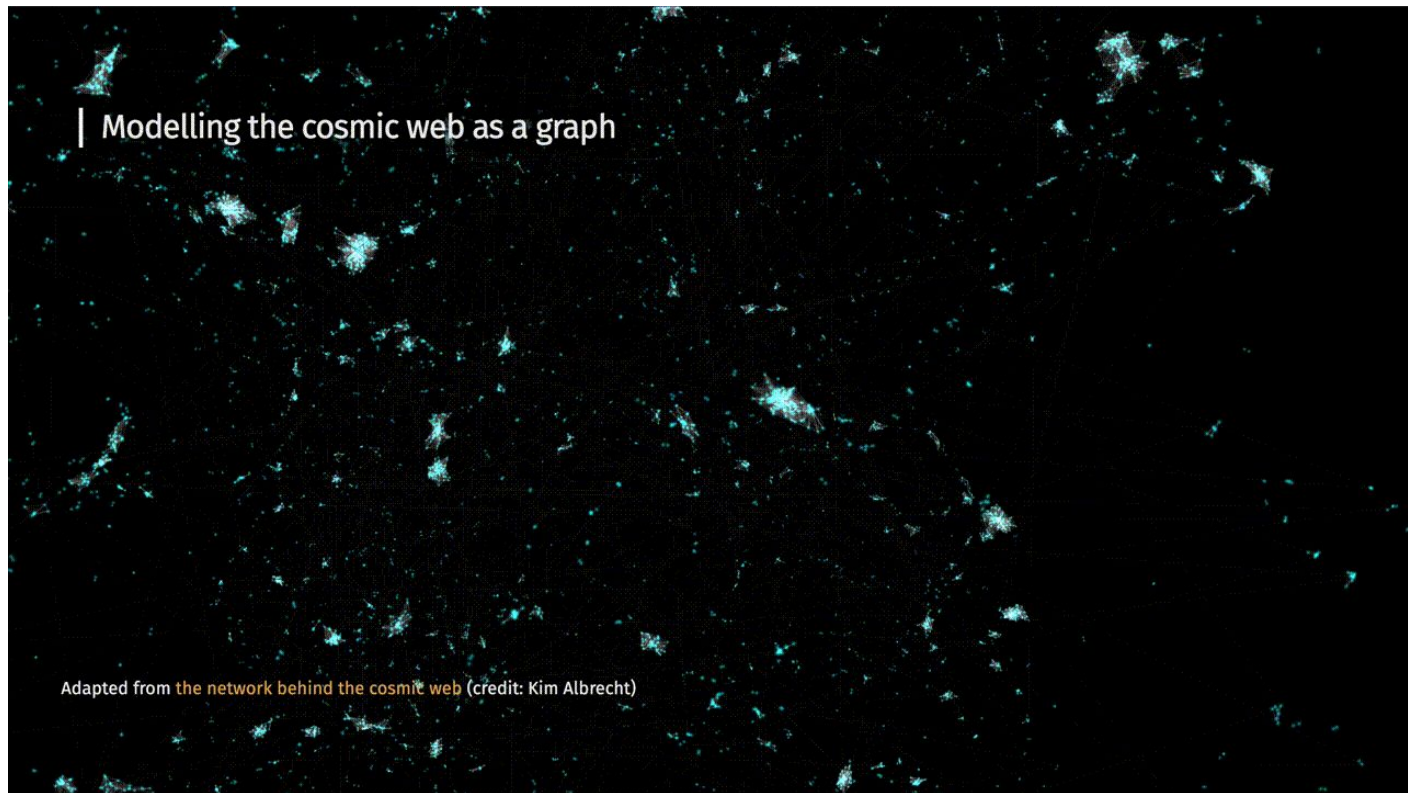
Text

Graph Neural Networks (GNN)

Convolutional Neural Networks (CNN)

Recurrent Neural Networks (RNN)

Graph neural networks: the right tool for galaxy distributions and the cosmic web

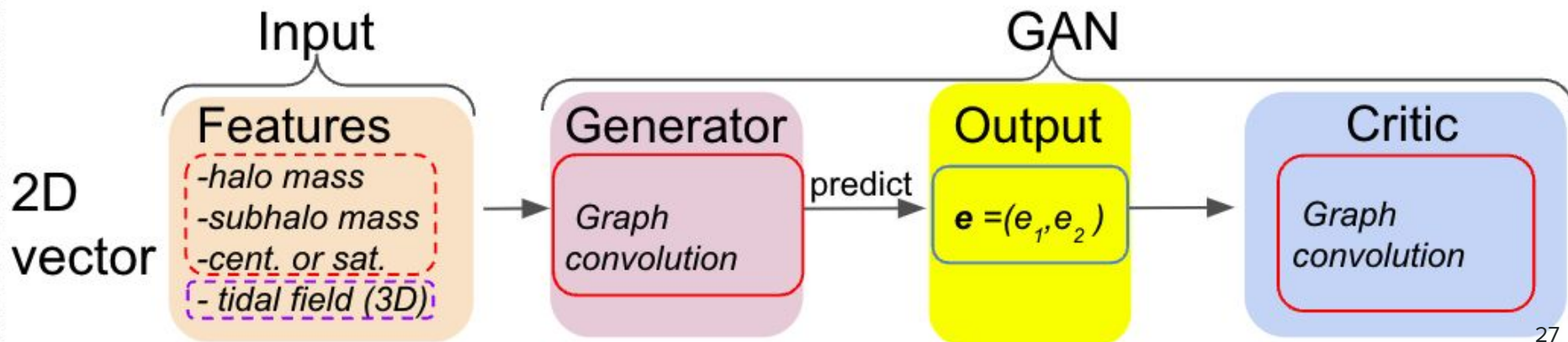


Approach: what information to use?

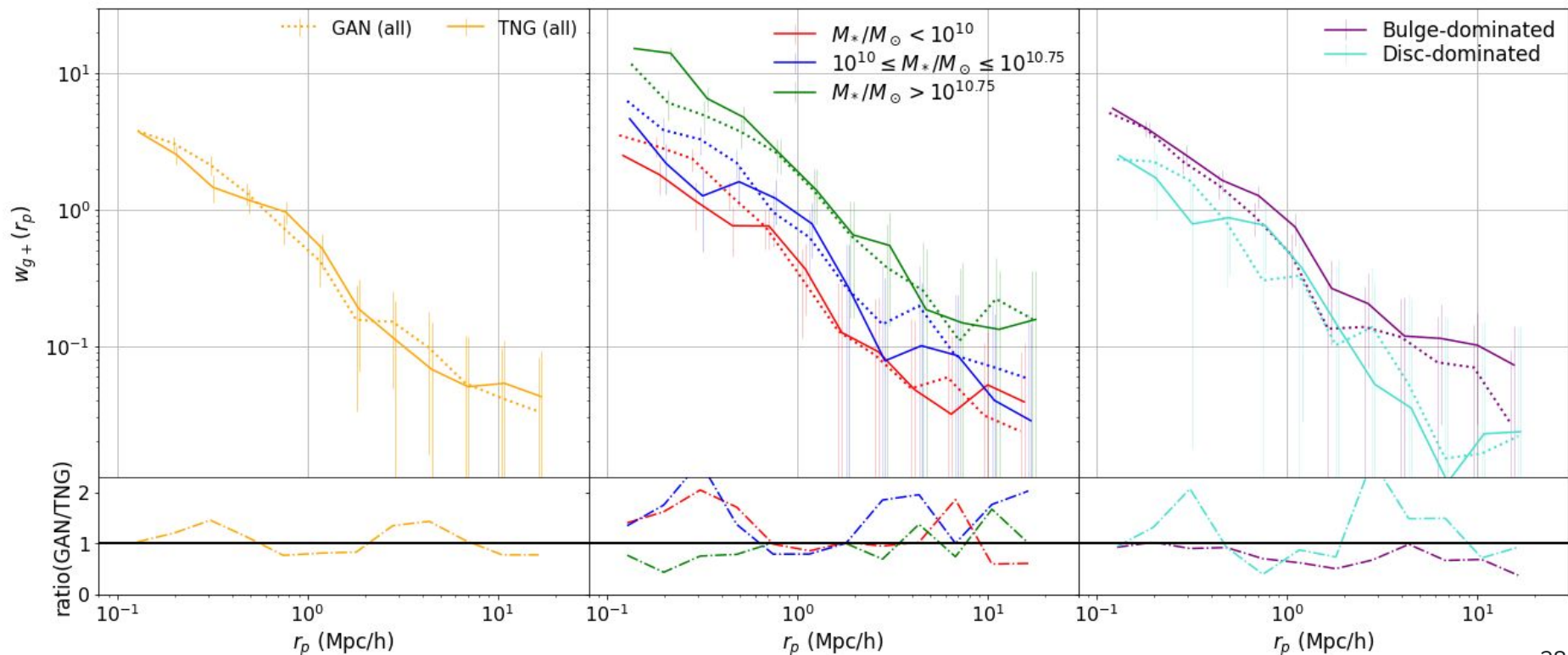
We use specific galaxy information to learn small-scale behavior on the graph and large-scale behavior from tidal fields.

Image credit: Jagvaral et al. (2022),

<https://ui.adsabs.harvard.edu/abs/2022MNRAS.516.2406J/abstract>

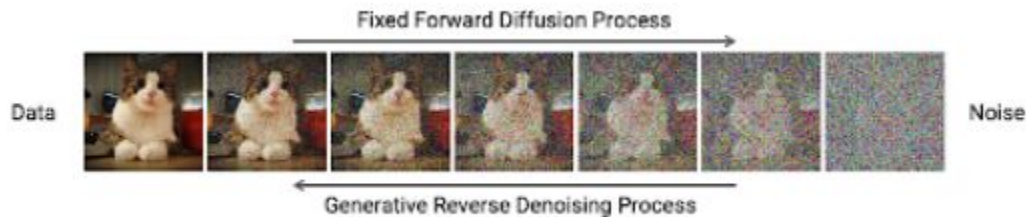


The model can then reproduce IA statistics for IllustrisTNG



This is nice, but ...

- The model doesn't know about symmetries on a sphere or 3D orientations
- The model does not use the latest innovations in generative models (diffusion models etc.)
- The tests are done at very high resolution. What about if subhalos hosting our galaxies are not resolved?
 - That's next... Requires novel algorithm development: recently accepted CS conference papers, will work on a demonstration in cosmological simulations next.



Diffusion generative models: algorithm development to work on the sphere!

Image credit: NeurIPS paper (to appear on
arxiv shortly) Jagvaral, Lanusse, & RM

We showed that we can reproduce strong
image patterns on the sphere...

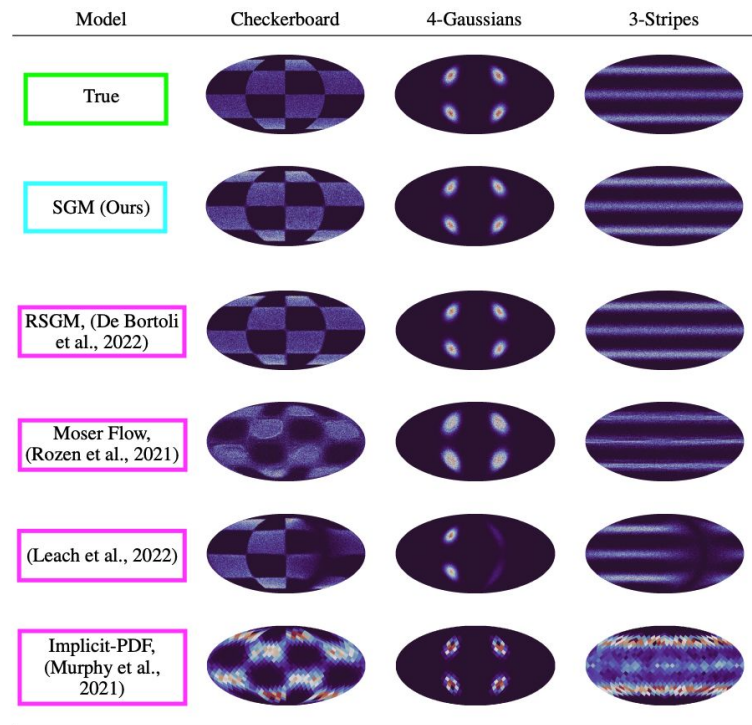
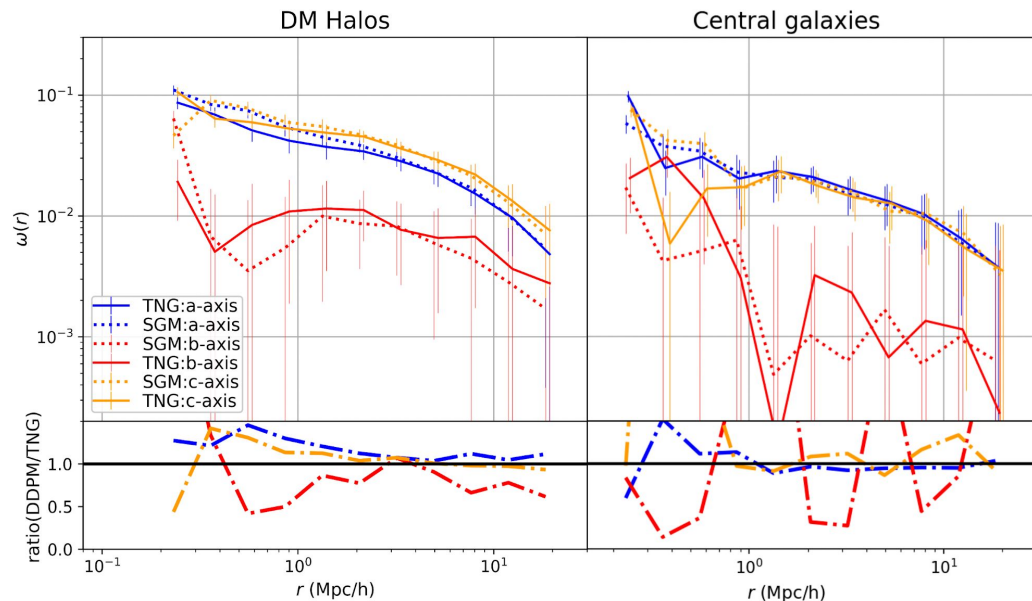


Figure 3: Density plot comparing samples from learned synthetic densities on $SO(3)$. For visualization this density plot shows the distribution of canonical axes of sampled rotations projected on the sphere; the tilt around that axis is discarded.

Diffusion generative models: algorithm development to work on the sphere!

But also that we can reproduce subtle
alignment patterns of dark matter halos....

Image credit: NeurIPS paper (to appear on
arxiv shortly) Jagvaral, Lanusse, & RM



So this is ready to go, right???

Not quite: we have to implement the graph layer within this model or use some other prescription for the 1-halo term. Ongoing work...

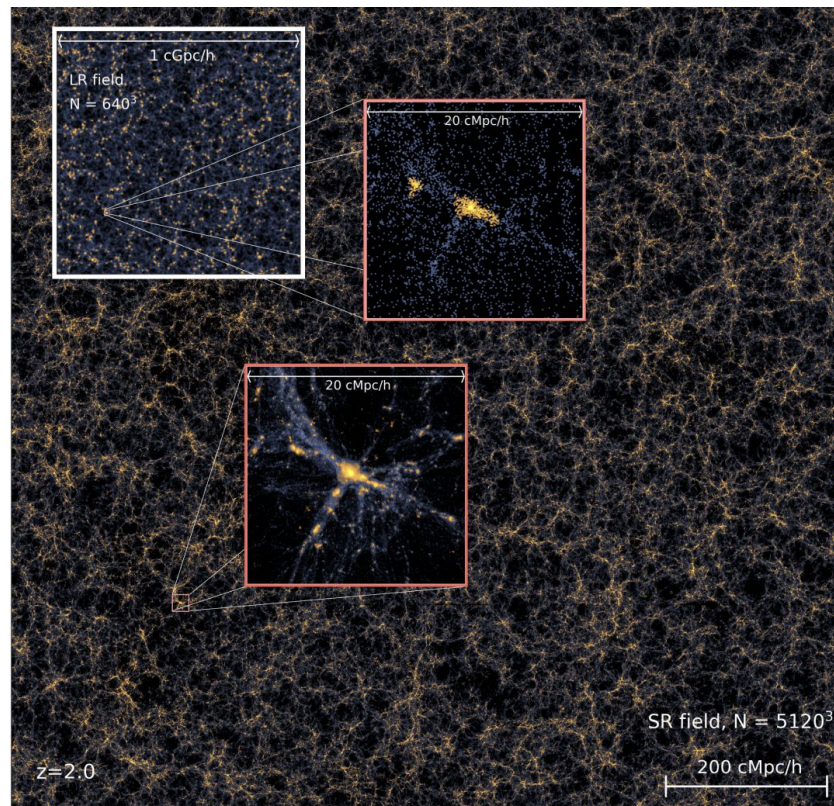
Also have to confront lower-resolution simulations and those with varying information available.

- Calculation of properties on the fly when generating sims: think ahead – we want halo shapes and tidal fields

Super-resolution: could this be useful in future?

Using a small number of high-resolution simulations to learn the small-scale structure, then apply that model to low-res simulations

Image credit: Yin Li et al (2020),
<https://arxiv.org/abs/2010.06608>

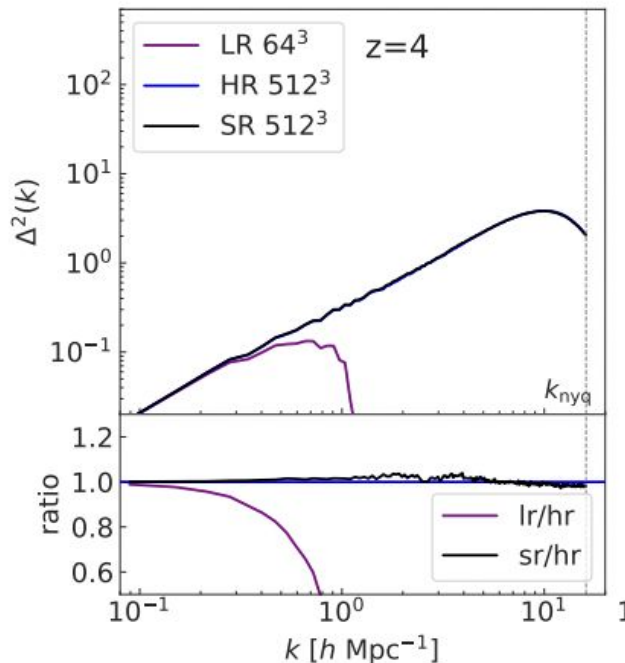


Super-resolution: could this be useful in future?

Using a small number of high-resolution simulations to learn the small-scale structure, then apply that model to low-res simulations

Image credit: Yin Li et al (2020),
<https://arxiv.org/abs/2010.06608>

It can recover the 2-point statistics quite accurately. Work is ongoing on higher-order statistics, halo properties.



Conclusions

- Despite their limitations, hydrodynamical simulations remain an important tool for understanding galaxy IA, and can guide us towards useful observational studies as well
- Deep learning is going to be an essential tool in developing non-parametric IA simulations for validating WL cosmological analysis methods in upcoming surveys