Using deep learning to predict the properties of galaxy mergers in EAGLE simulations.

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Supervisor : Maxwell Cai

What are galaxy mergers and why are they important?

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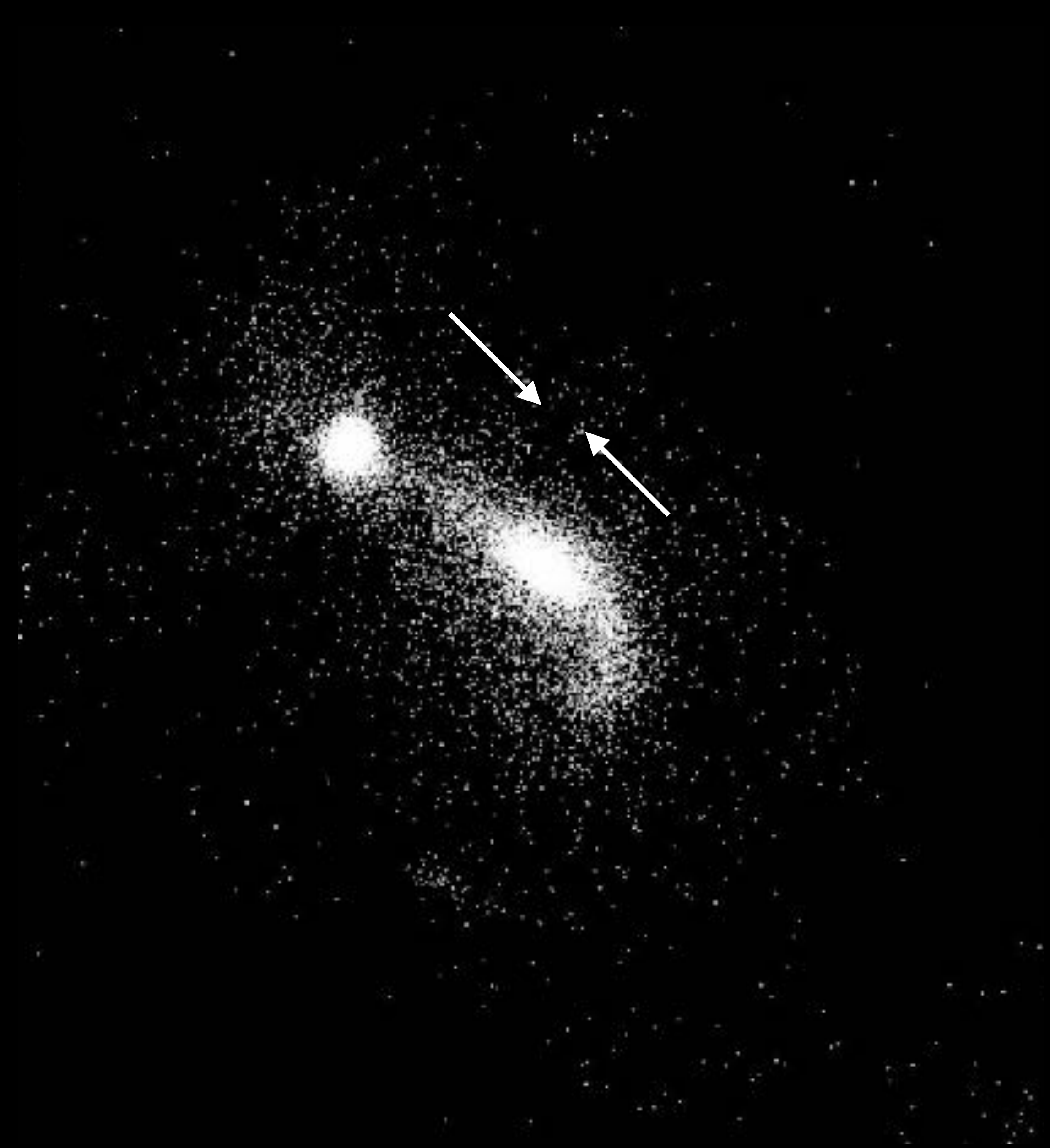
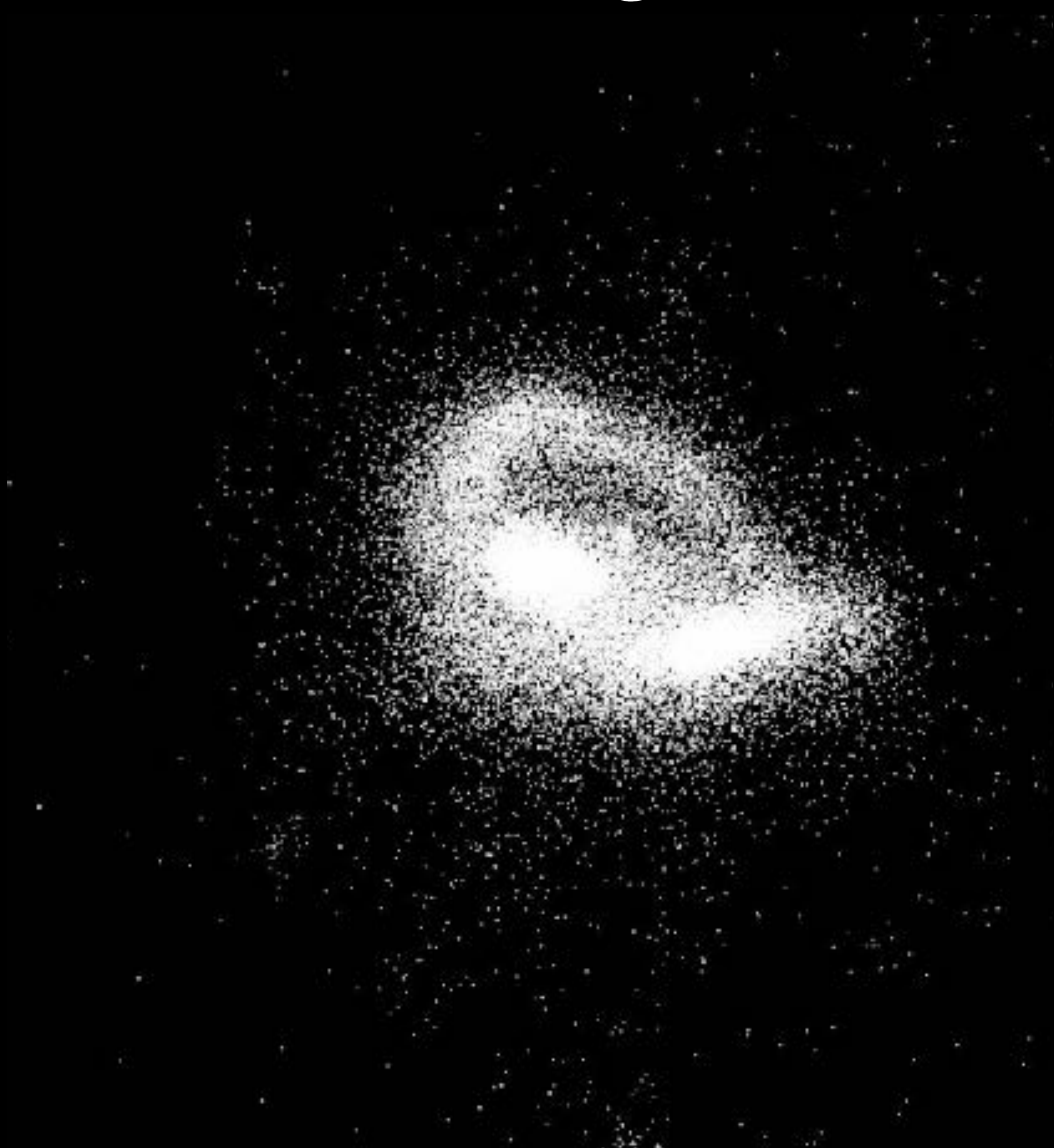


Collisions

What are galaxy mergers and why are they important?

1. Mass growth



Accretion

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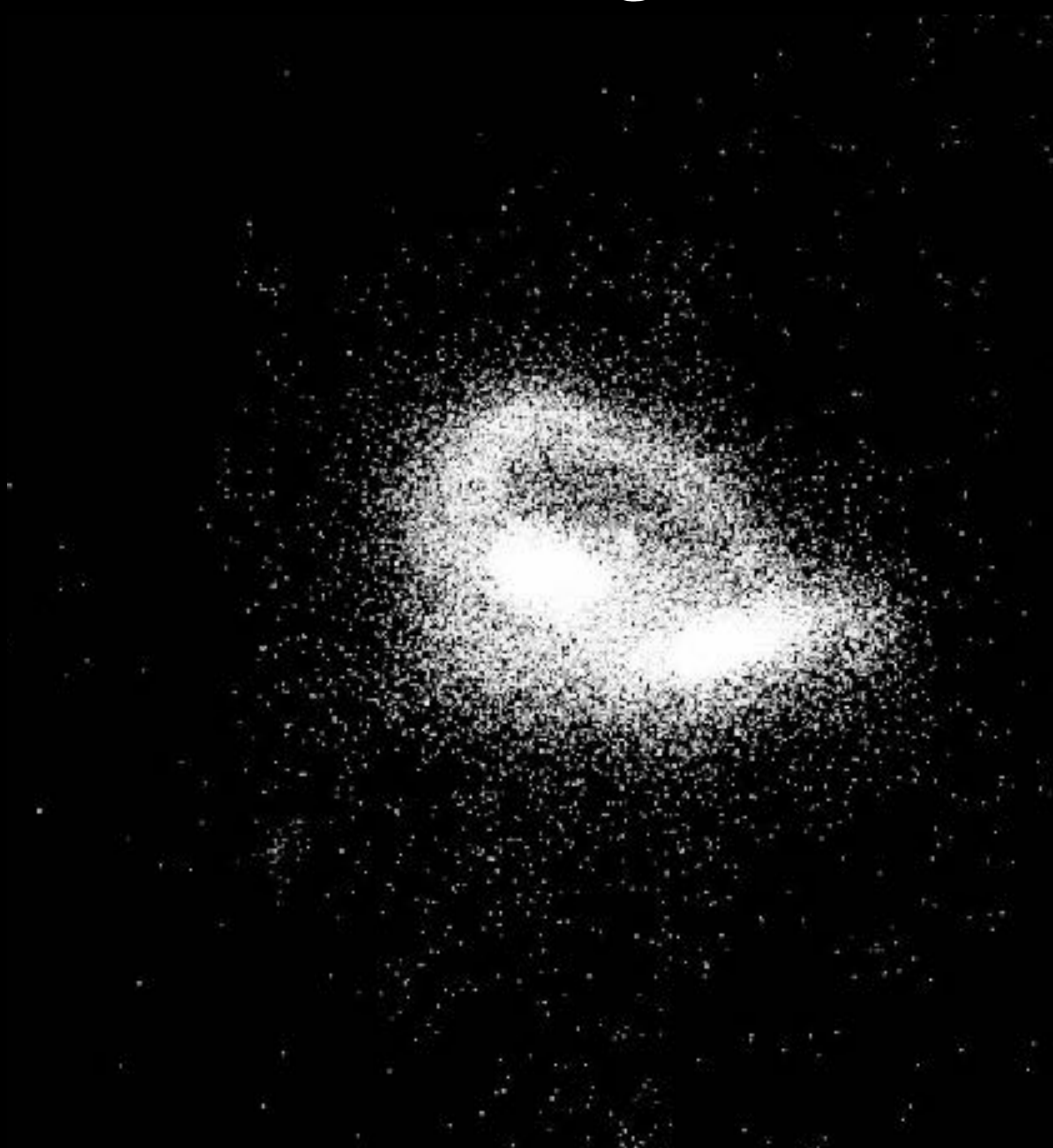
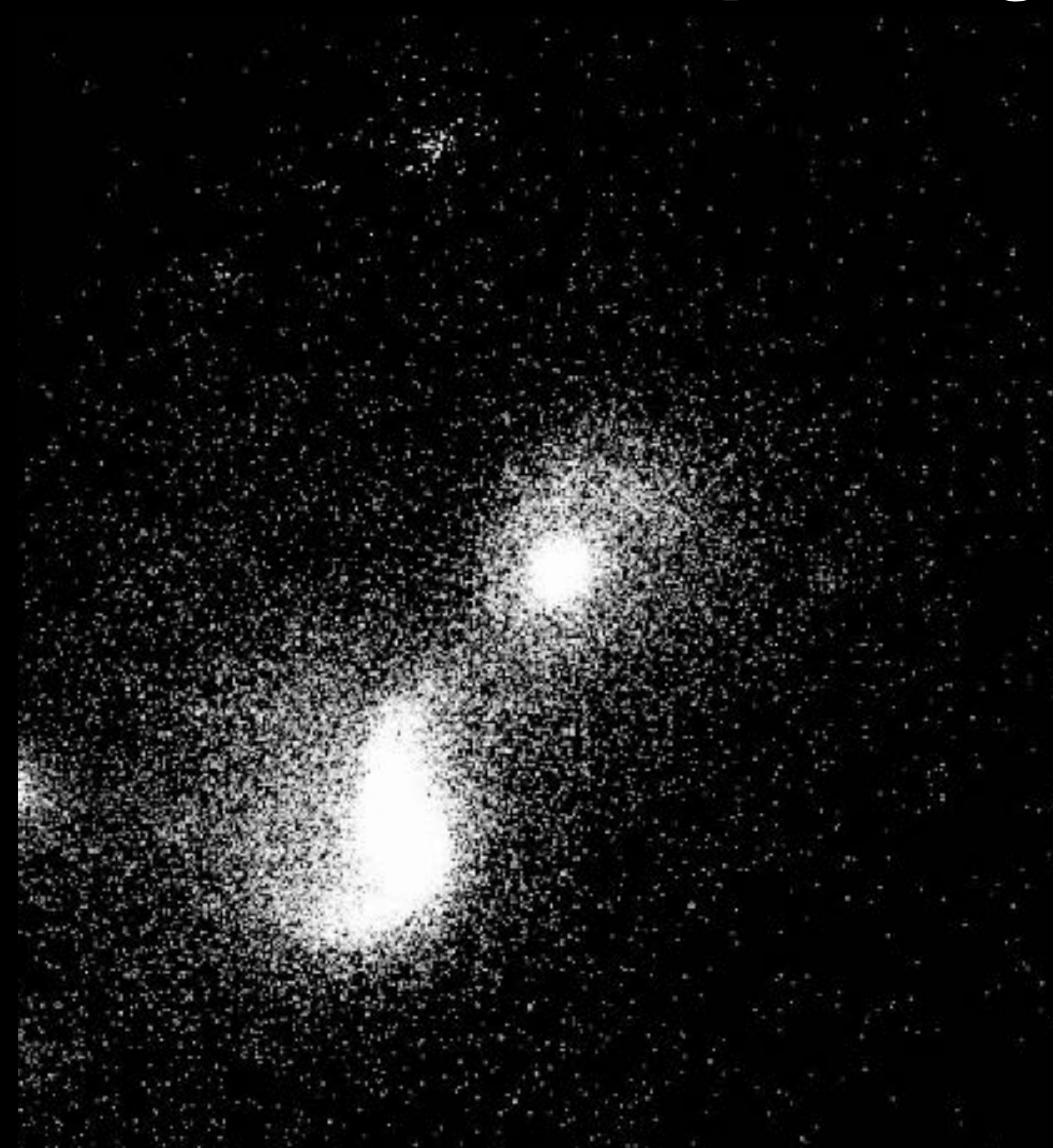


Accretion

2. Effect on Morphology



Disk to spheroidal - gas poor
Disk retained - gas rich

Aim of this project

To train a deep neural network that is able to learn from galaxy merger images from EAGLE simulations and predict the relative properties like mass and size ratio of the progenitor galaxies involved in the merger.

Two phases-

1. Visualising galaxy mergers. ($z=0$ and $z>0$)

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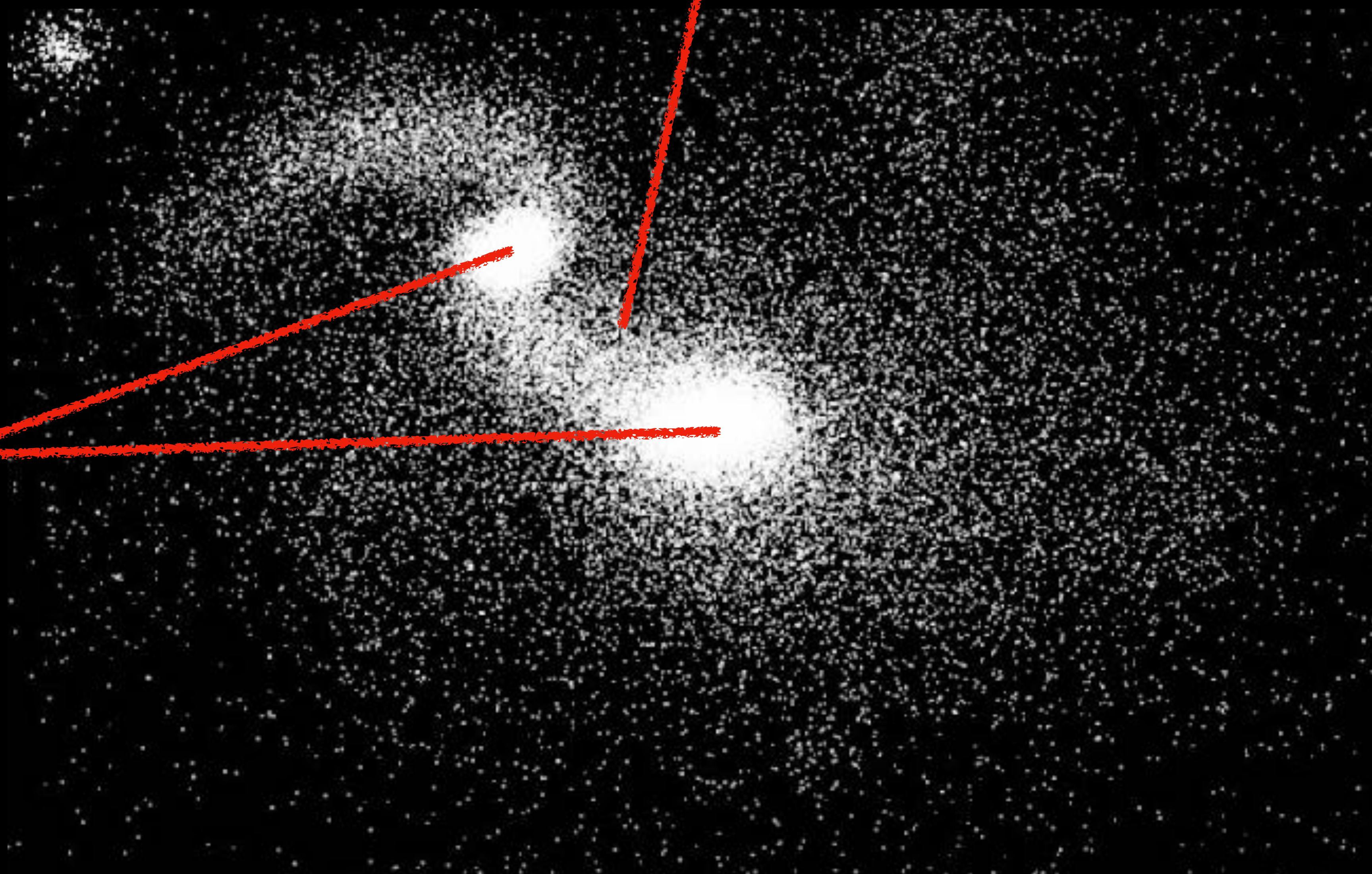
EAGLE simulations

merging centre

Centre of Potential



A galaxy merger

Why do we need simulations?

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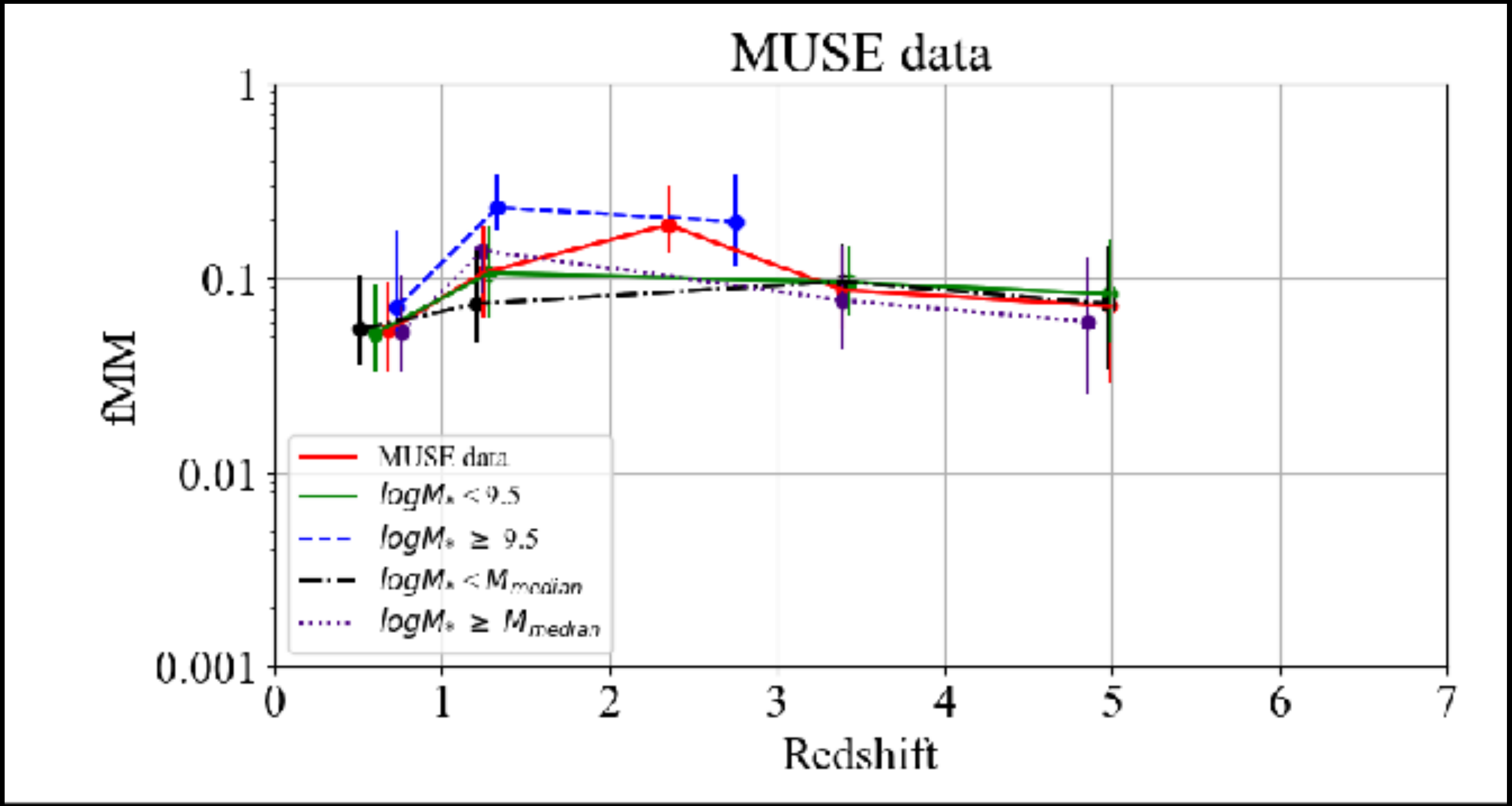
- Mergers are rare

Why do we need simulations?

- Mergers are rare

$$fMM = \frac{number\ of\ galaxy\ mergers}{total\ number\ of\ galaxies\ in\ that\ redshift}$$



E.Ventou et al.2017

Why do we need simulations?

- We can infer observed galaxy merger properties with simulation data.

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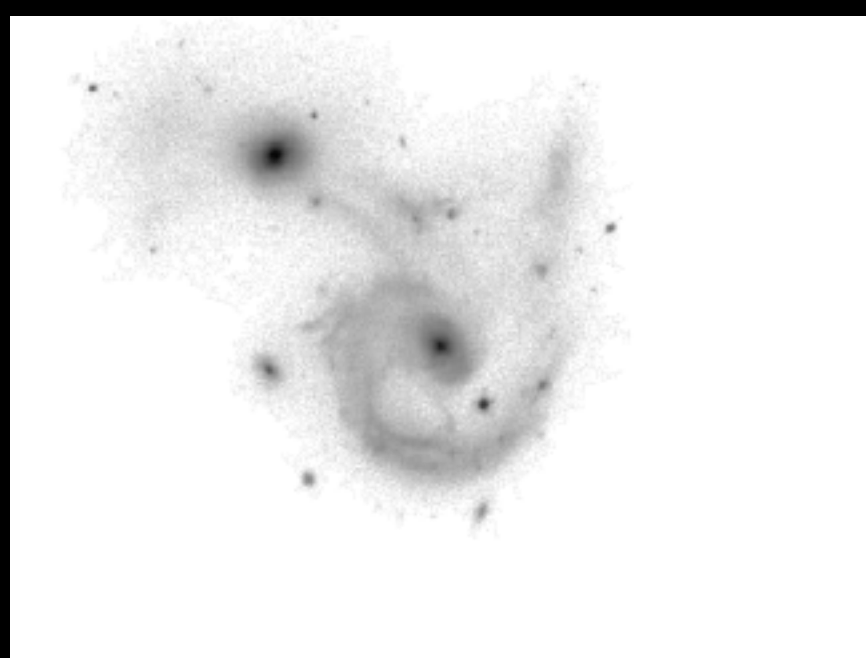
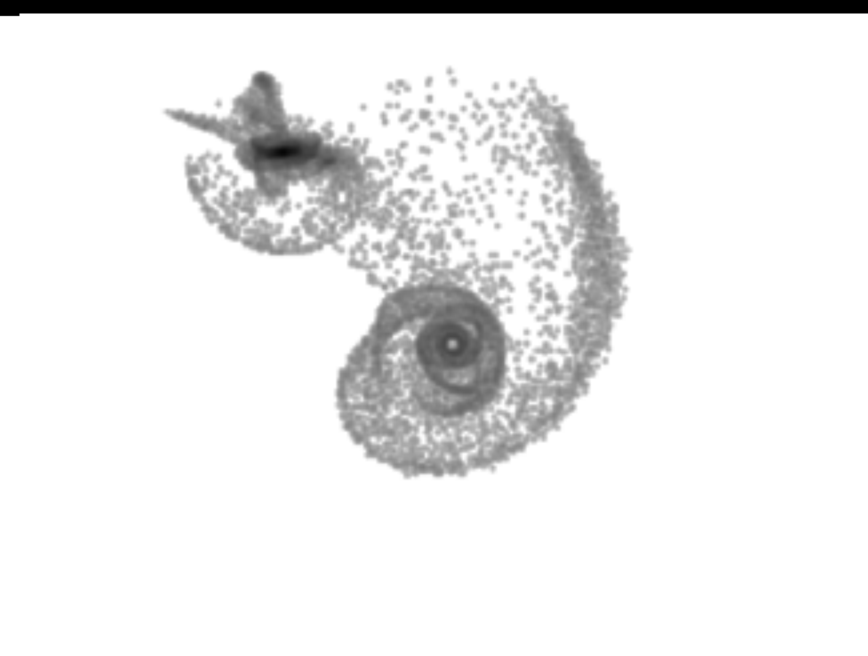


Merger

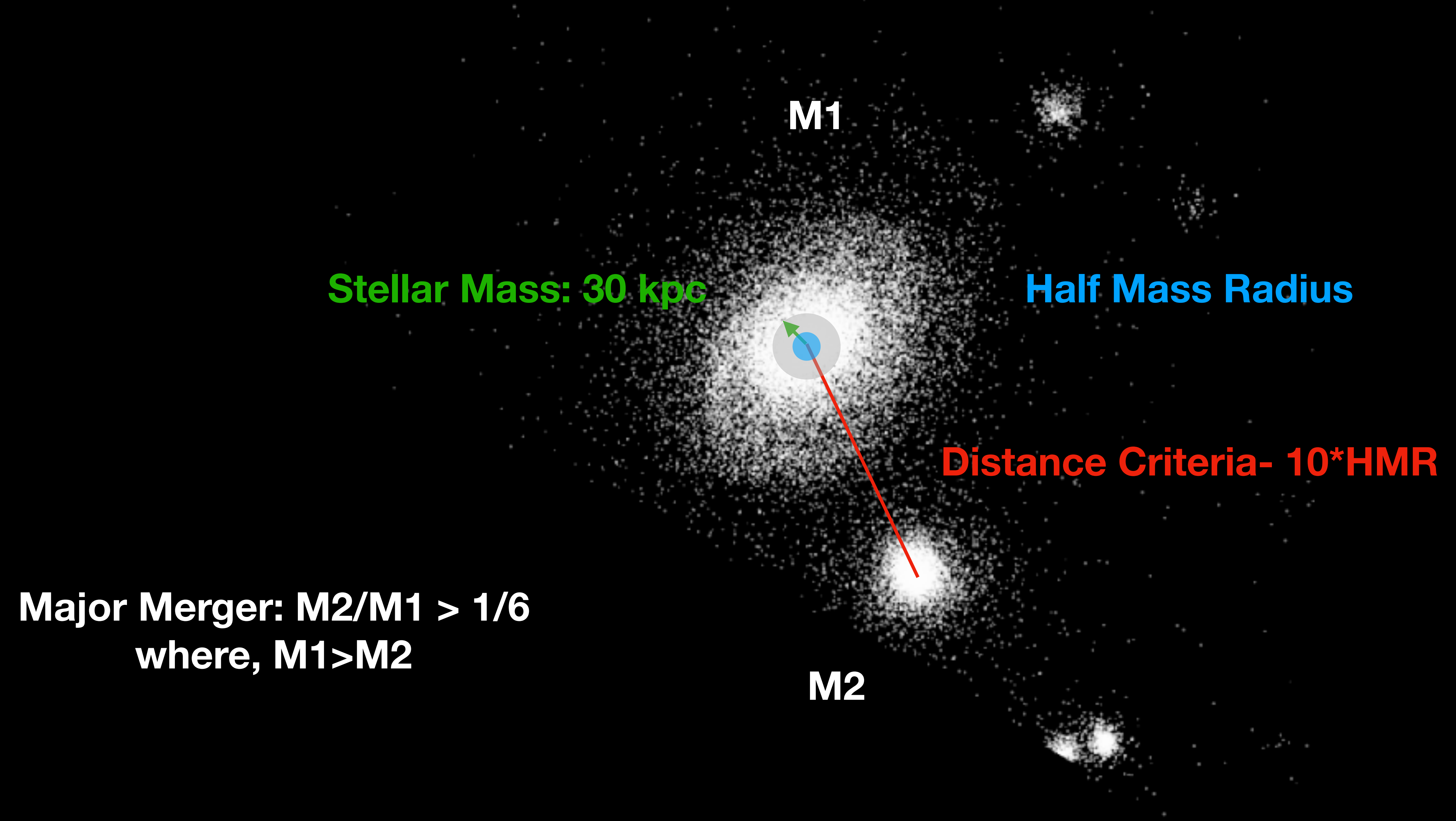


Simulation

Fig. Galaxy Zoo: Mergers project- https://data.galaxyzoo.org/galaxy-zoo-mergers/targets/index.html

Assumptions

$all\ M > 10^9 M_\odot$



galaxy merger criteria

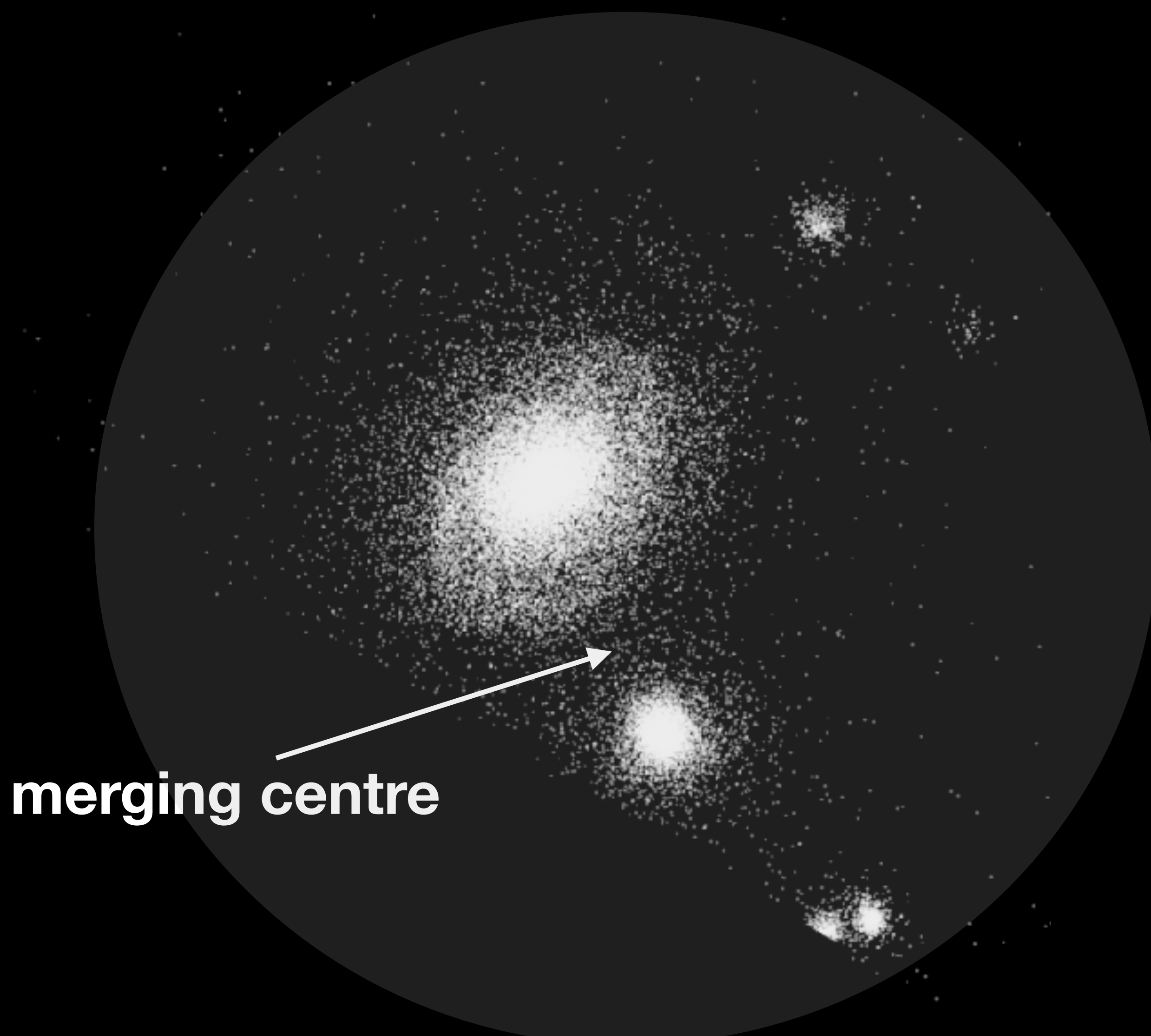
Visualisation

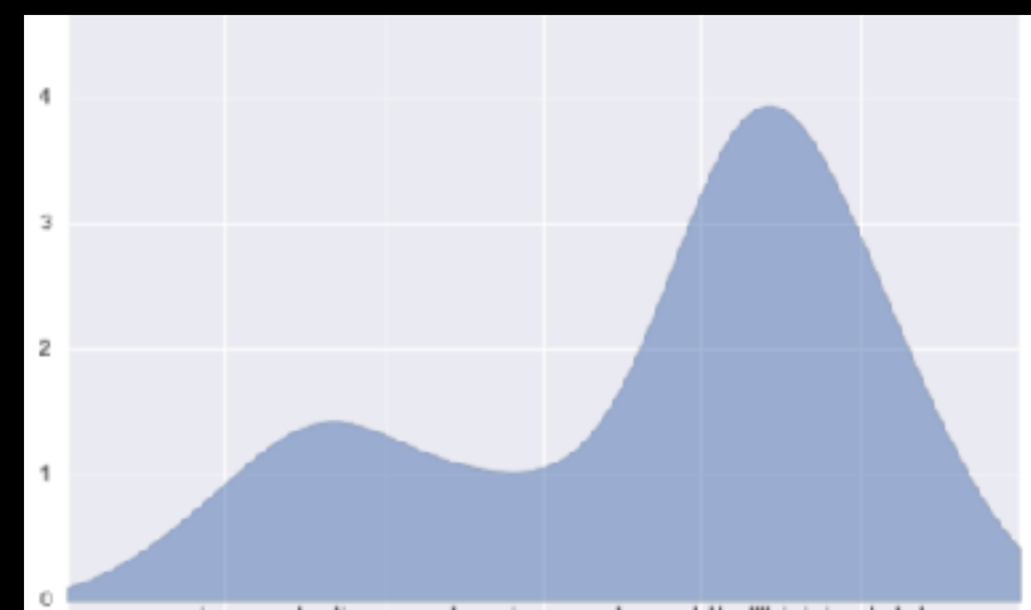
SnapNum	Redshift	Lookback time	Expansion factor
28	0.00	0.00	1.000
27	0.10	1.34	0.909
26	0.18	2.29	0.846
25	0.27	3.23	0.787
24	0.37	4.16	0.732
23	0.50	5.19	0.665
22	0.62	6.01	0.619
21	0.74	6.71	0.576
20	0.87	7.37	0.536
19	1.00	7.93	0.499
18	1.26	8.86	0.443
17	1.49	9.49	0.402
16	1.74	10.05	0.365
15	2.01	10.53	0.332
14	2.24	10.86	0.309
13	2.48	11.16	0.287
12	3.02	11.66	0.249
11	3.53	12.01	0.221
10	3.98	12.25	0.201
9	4.49	12.46	0.182
8	5.04	12.63	0.166
7	5.49	12.75	0.154
6	5.97	12.86	0.143
5	7.05	13.04	0.124
4	8.07	13.16	0.110
3	8.99	13.25	0.100
2	9.99	13.32	0.091
1	15.13	13.53	0.062
0	20.00	13.62	0.047

1. Identify galaxy mergers

2. Note the dark matter they belong to

3. Kernel Density Estimation- estimate merger centre

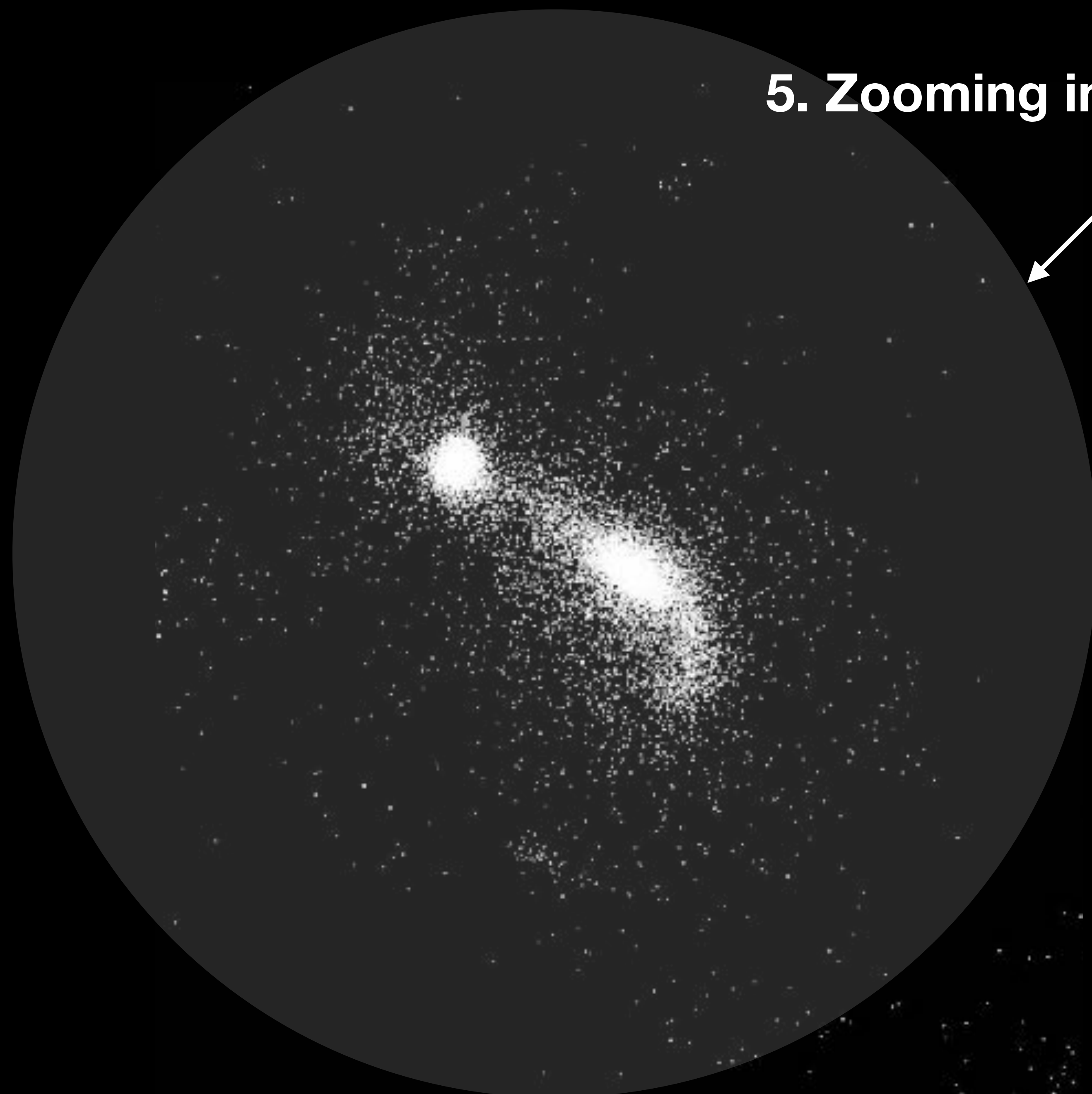




Peaks- dense regions in the DM halo

4. Calculate the merger centre of the galaxy merger

5. Zooming into the Dark matter halo



Galaxy merger in a dark matter halo,
EAGLE simulations

Two ways of zooming:

z=0, EAGLE package →

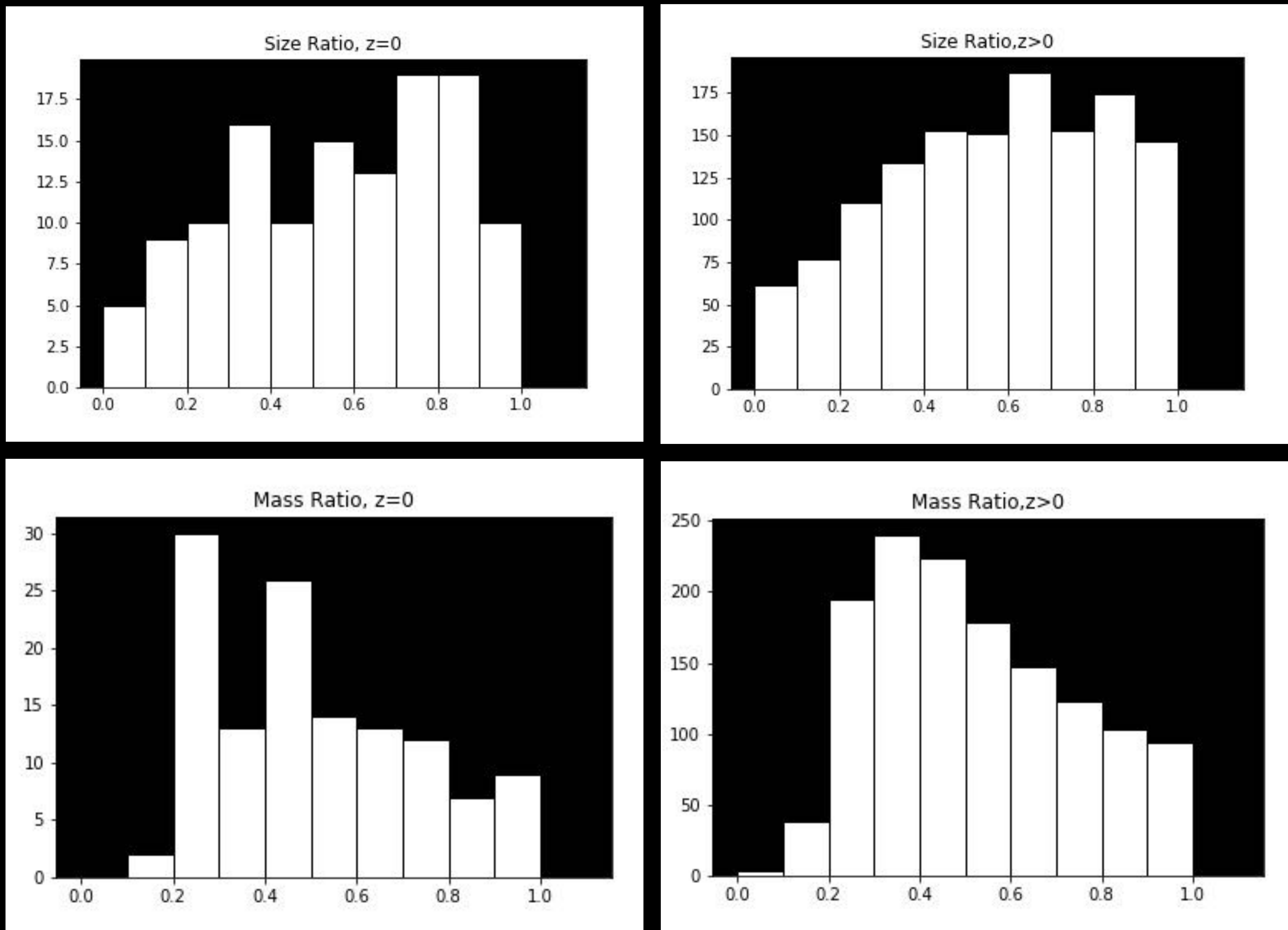
25*25 kpc

35*35 kpc

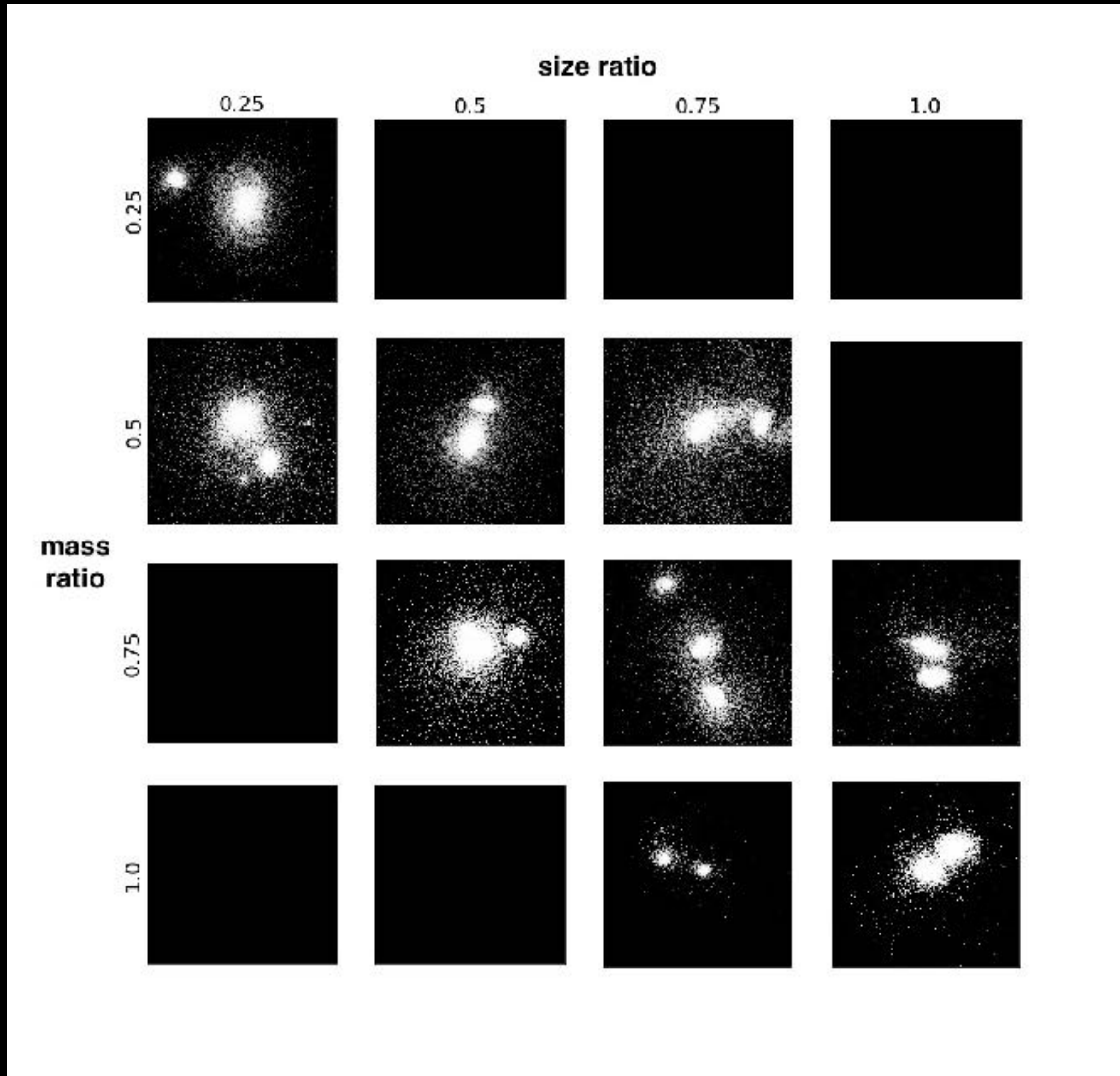
← **z>0, self written code**

Properties

- In this thesis, we pick the most visually apparent properties namely the -
  - Mass ratio
  - Size ratio
- Number of classes = [0.25,0.5,0.75,1.0]



Size Ratio, z=0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0.0 0.2 0.4 0.6 0.8 1.0
Size Ratio,z>0
175
150
125
100
75
50
25
0
0.0 0.2 0.4 0.6 0.8 1.0
Mass Ratio, z=0
30
25
20
15
10
5
0
0.0 0.2 0.4 0.6 0.8 1.0
Mass Ratio,z>0
250
200
150
100
50
0
0.0 0.2 0.4 0.6 0.8 1.0



Galaxy mergers from EAGLE simulations

Two phases-

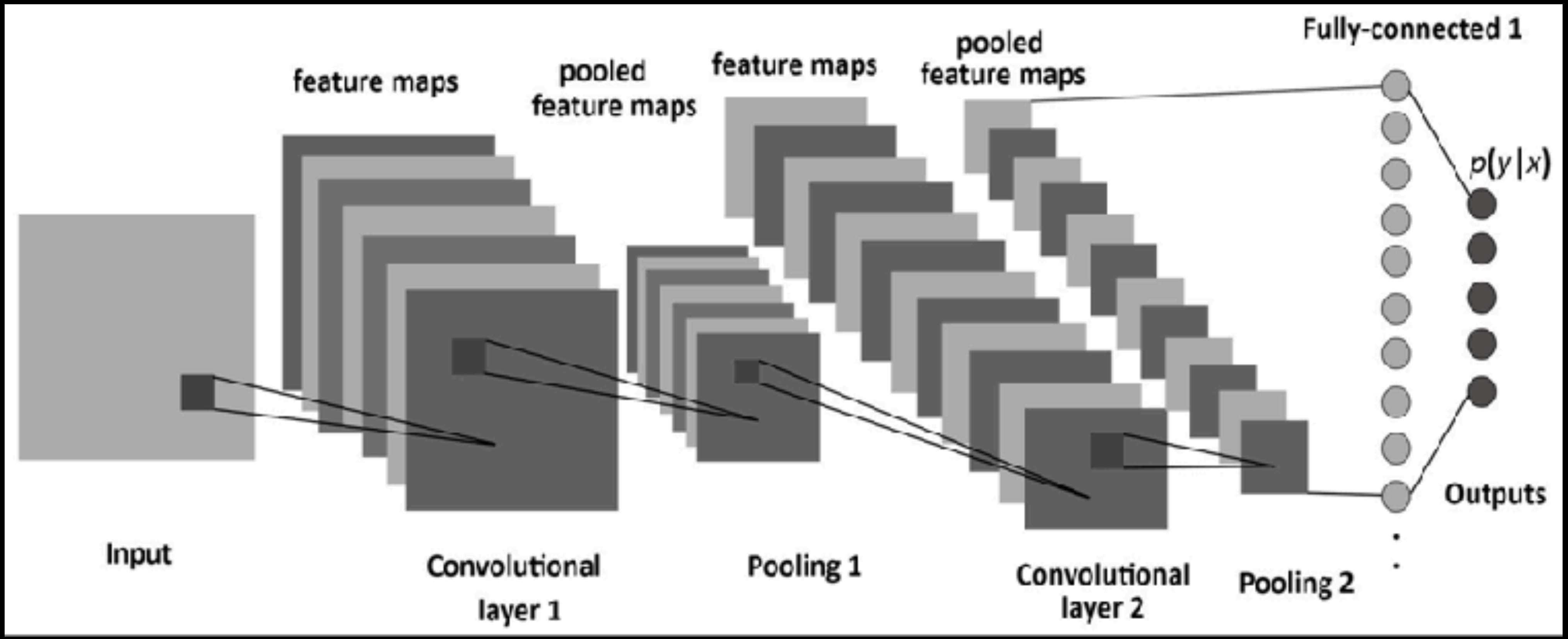
1. Visualising galaxy mergers. ($z=0$ and $z>0$)

2. Training a Deep Neural Network to predict properties from visualised mergers.

What is a Deep Neural Network (DNN)?

Img source:https://towardsdatascience.com/neural-quantum-states-4793fdf67b13

Feature selection- Image classification

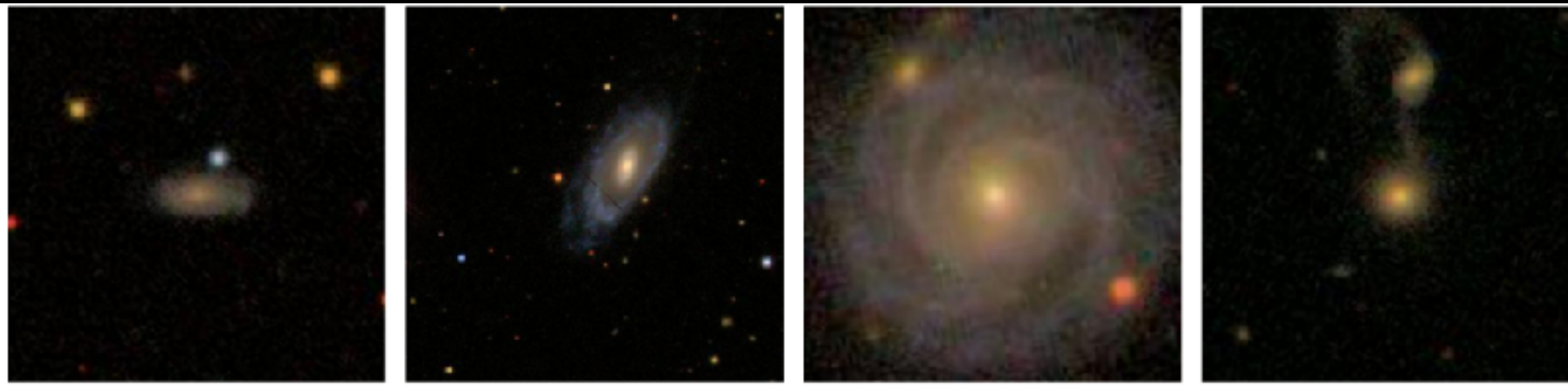


Img source: https://www.mdpi.com/1099-4300/19/6/242

Image classification in Astronomy

Image classification in Astronomy

DNN have been used in galaxy morphology classification before (Dieleman et al. 2015).



(a) 0.24610 (b) 0.21877 (c) 0.21145 (d) 0.20088

37 questions, RMSE

Image classification in Astronomy

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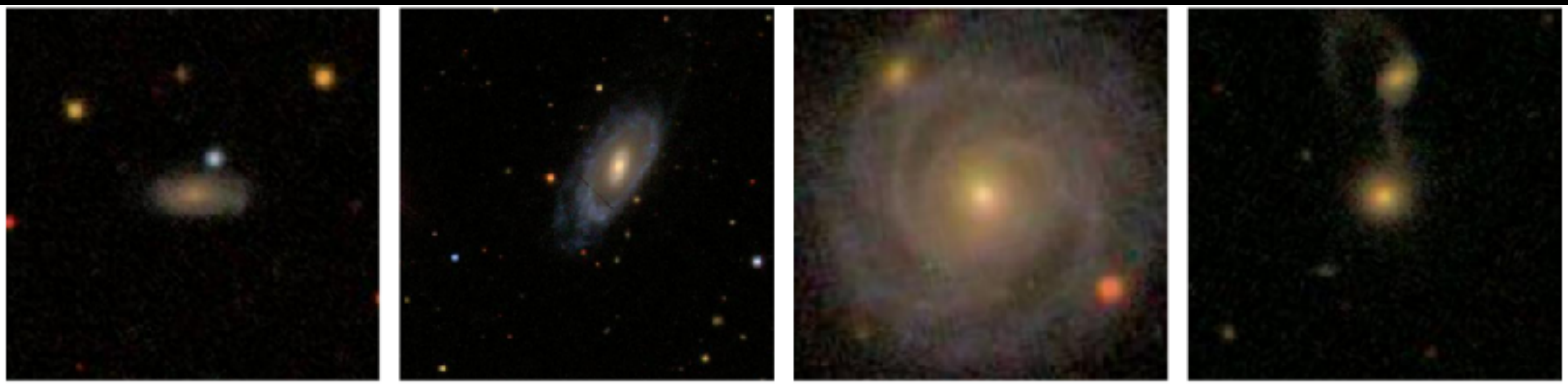


(a) 0.24610 (b) 0.21877 (c) 0.21145 (d) 0.20088

37 questions, RMSE

In this thesis, we go a step further and try to predict its properties.

Deep Neural Network

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
conv2d (Conv2D)	(None, 222, 222, 32)	896
dropout (Dropout)	(None, 222, 222, 32)	0
conv2d_1 (Conv2D)	(None, 220, 220, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 110, 110, 32)	0
dropout_1 (Dropout)	(None, 110, 110, 32)	0
flatten (Flatten)	(None, 387200)	0
dense (Dense)	(None, 128)	49561728
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 4)	516

Total params: 49,572,388
Trainable params: 49,572,388
Non-trainable params: 0

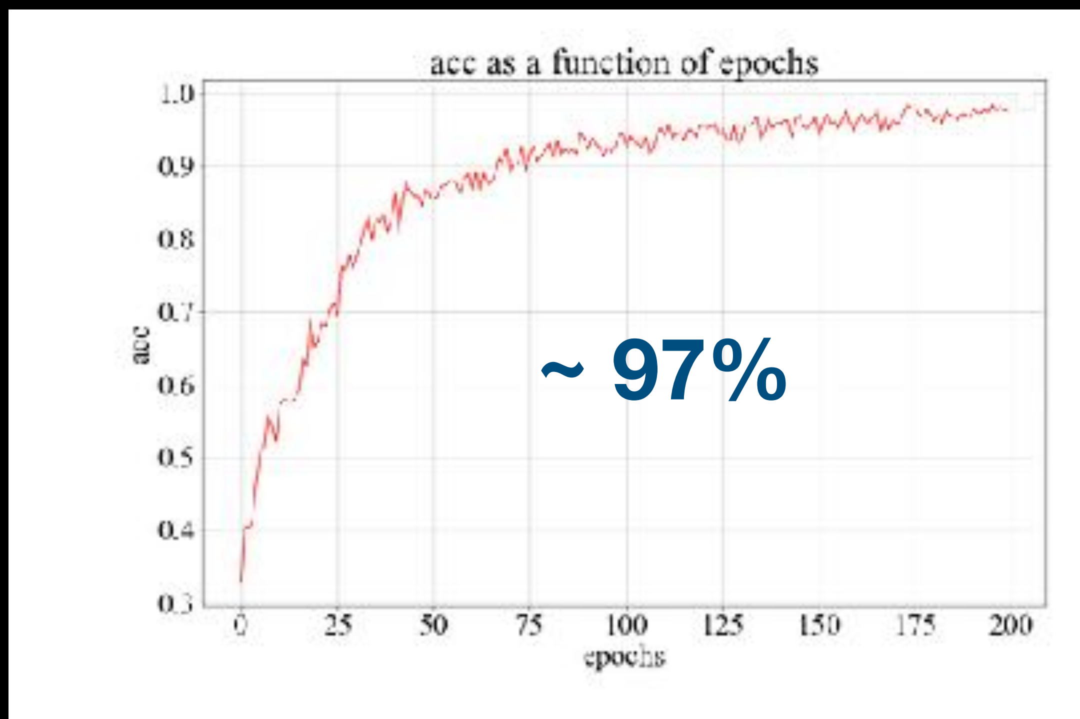
Based on keras example mnist_cnn.py

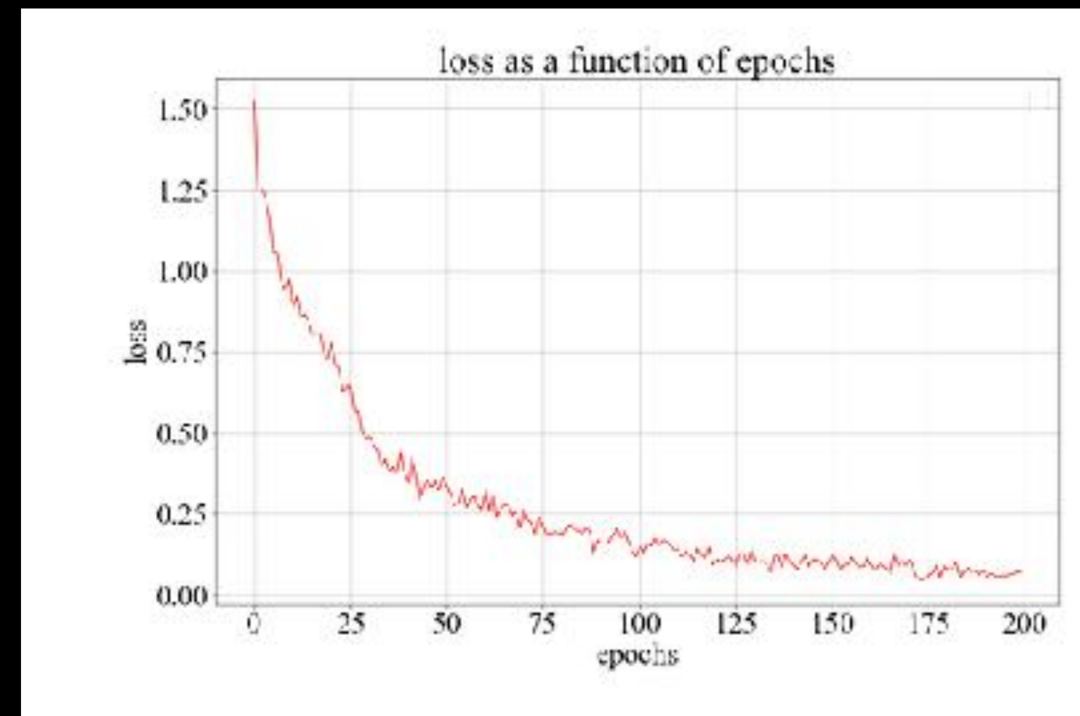
Results

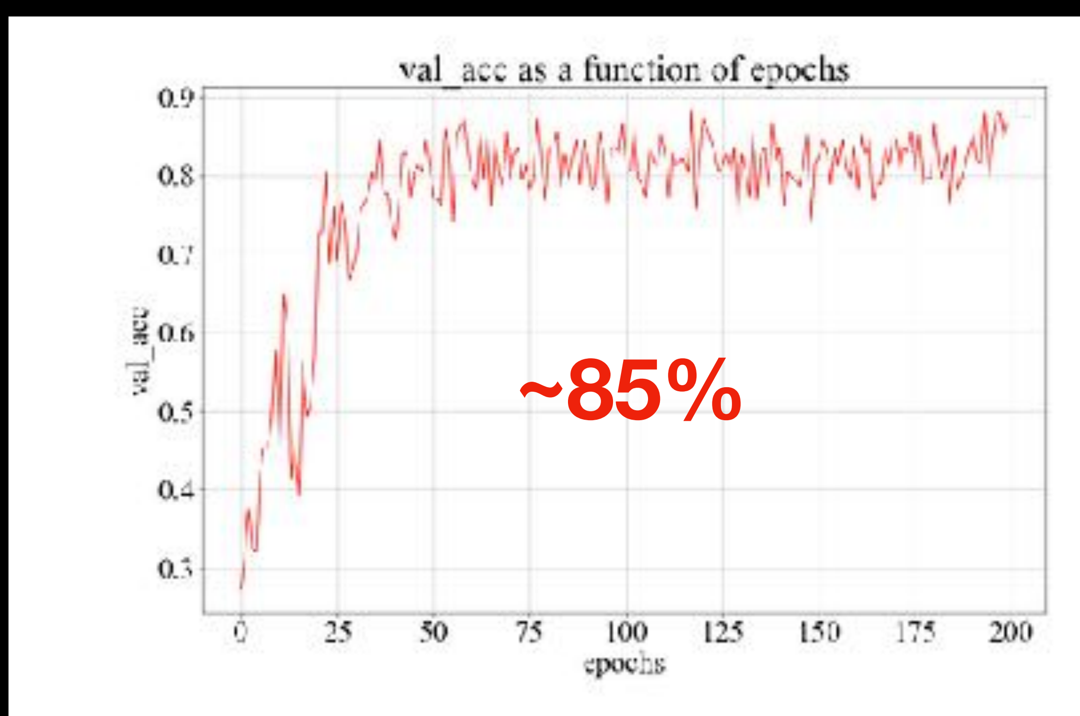
$$Loss(true, pred) = -\sum_{x} true(x) log(pred(x))$$

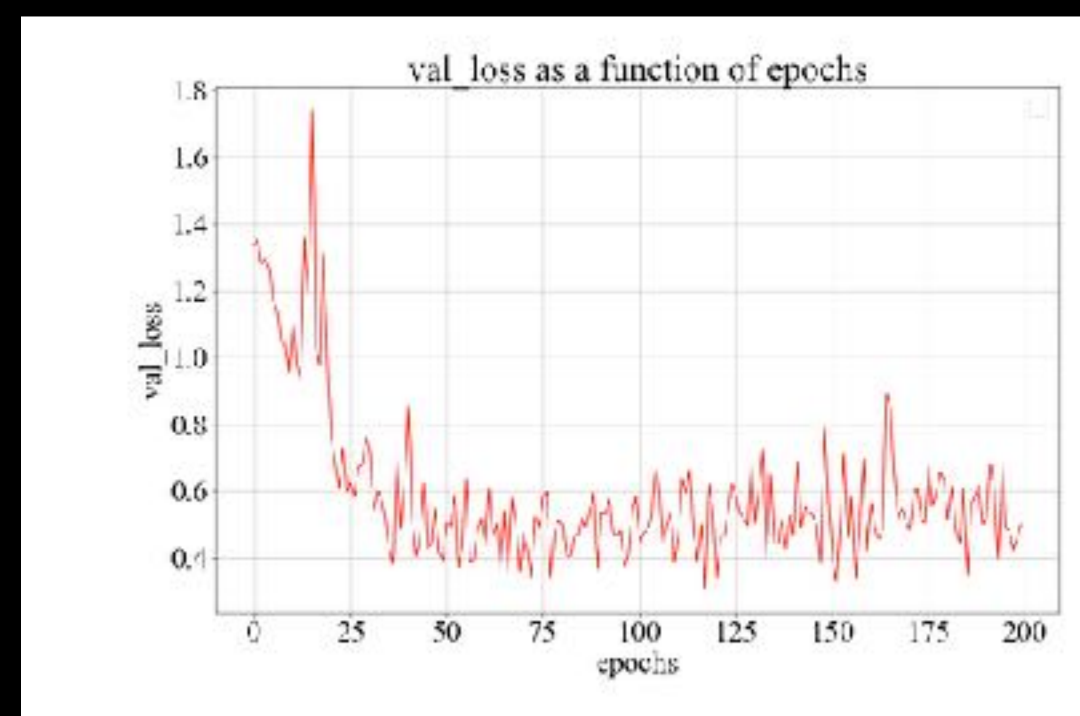
$$acc = \%\, of correct\ predictions$$

Mass Ratio, z=0





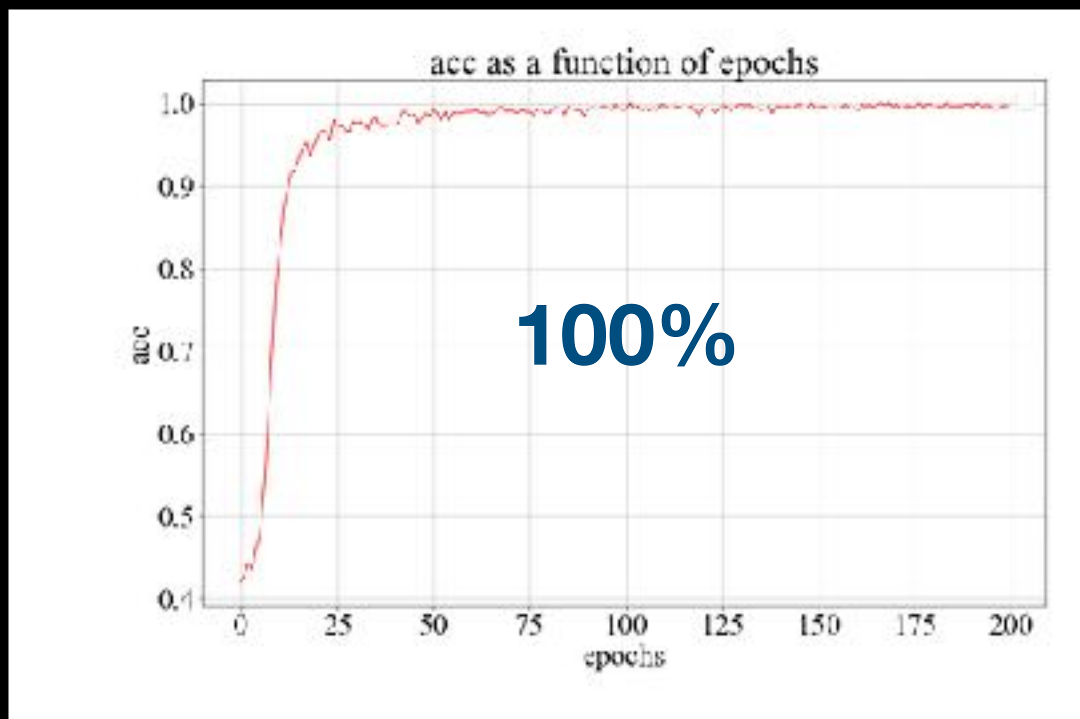


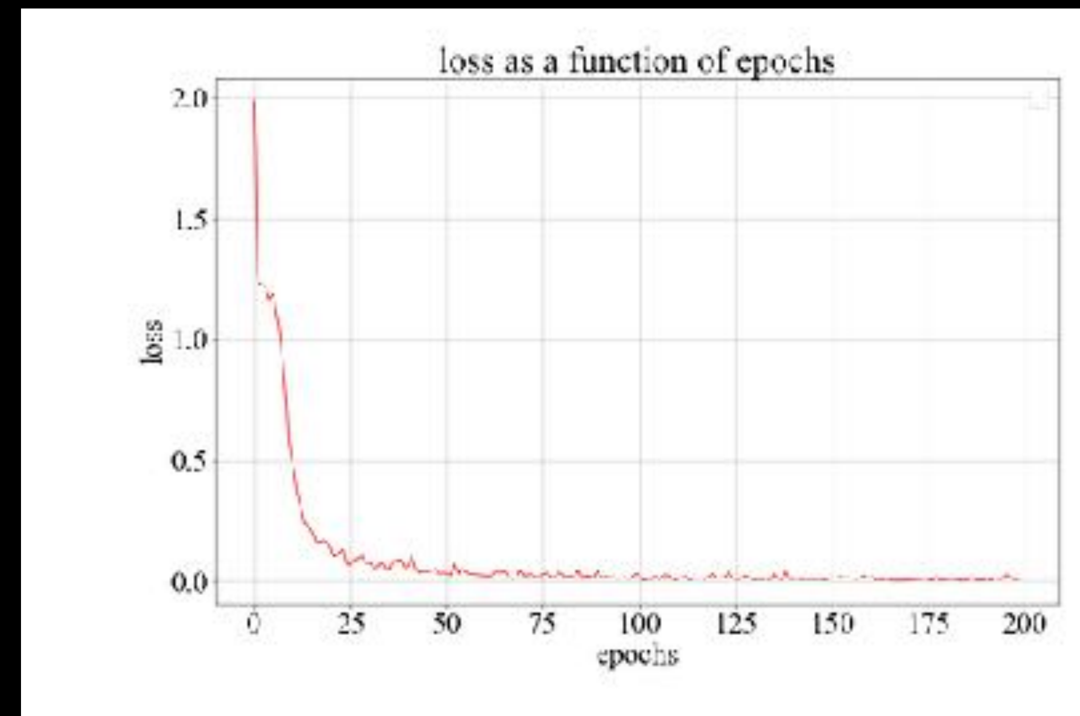


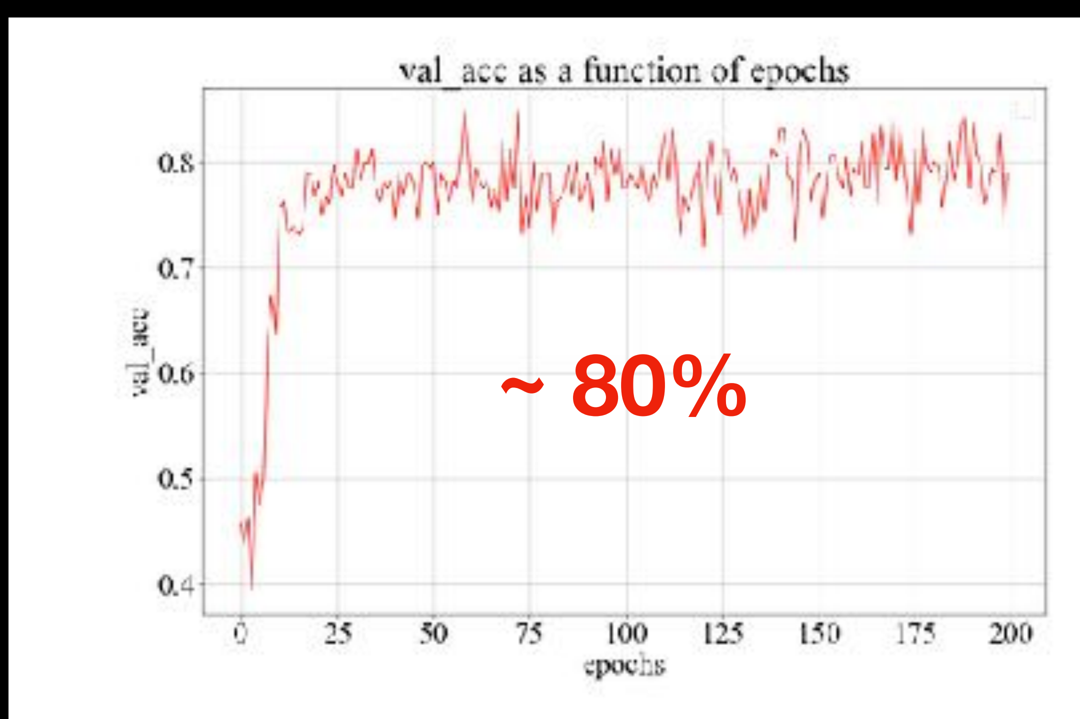
$$Loss(true, pred) = -\sum_x true(x) log(pred(x))$$

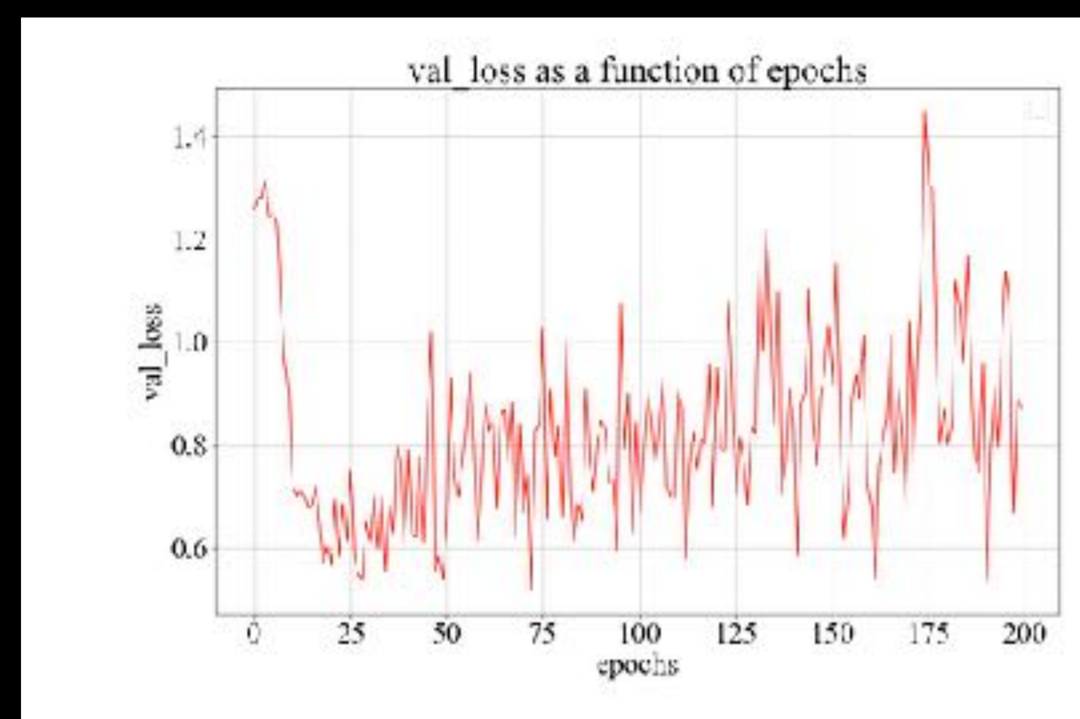
$$acc = \% \text{ of correct predictions}$$

Mass Ratio, z>0









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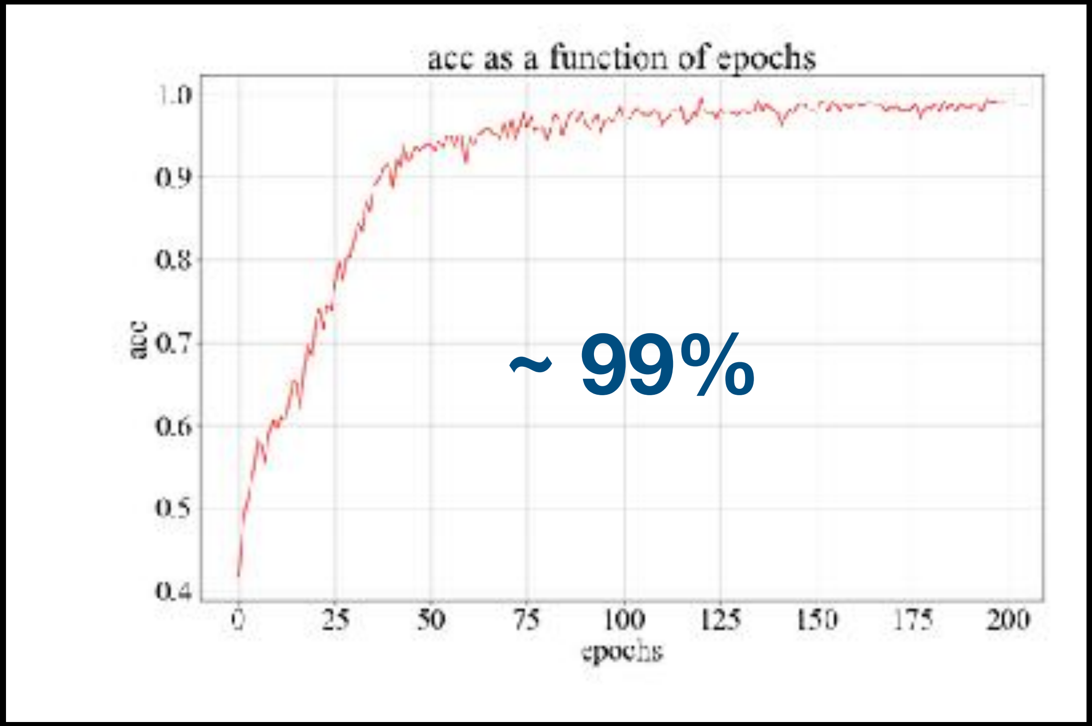
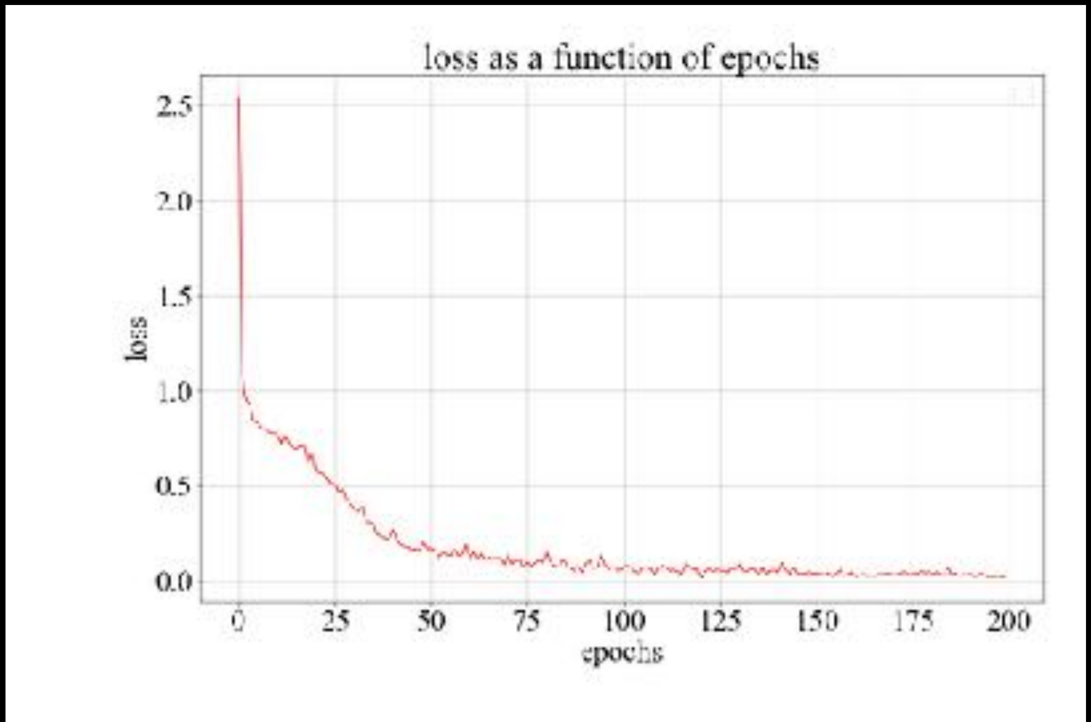
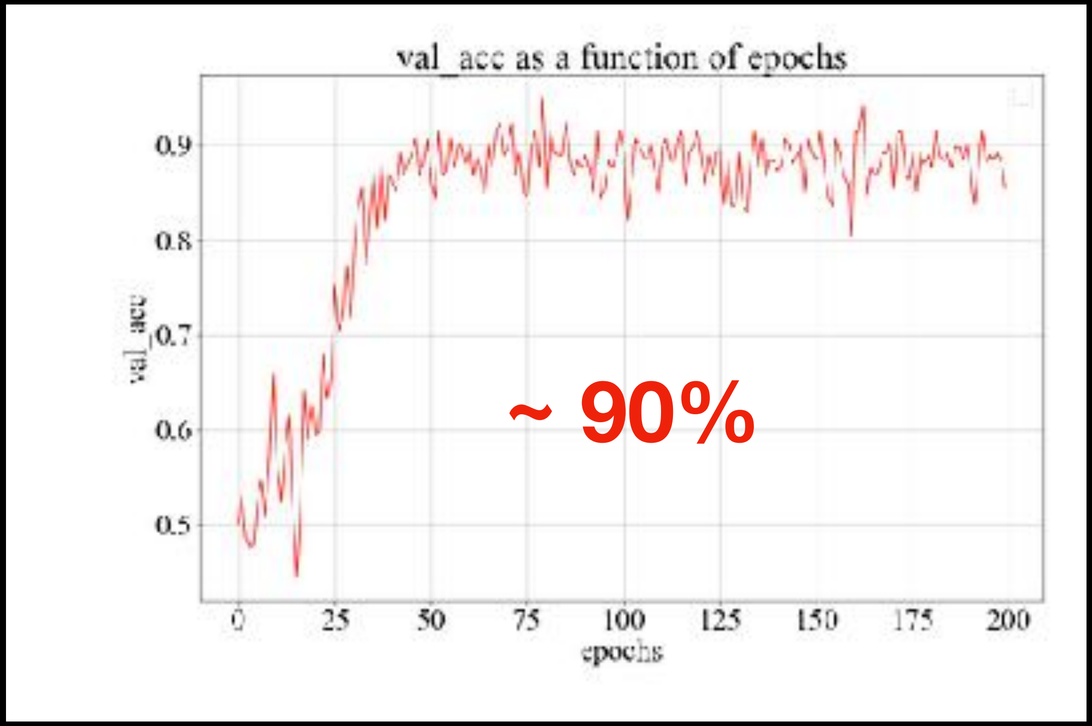
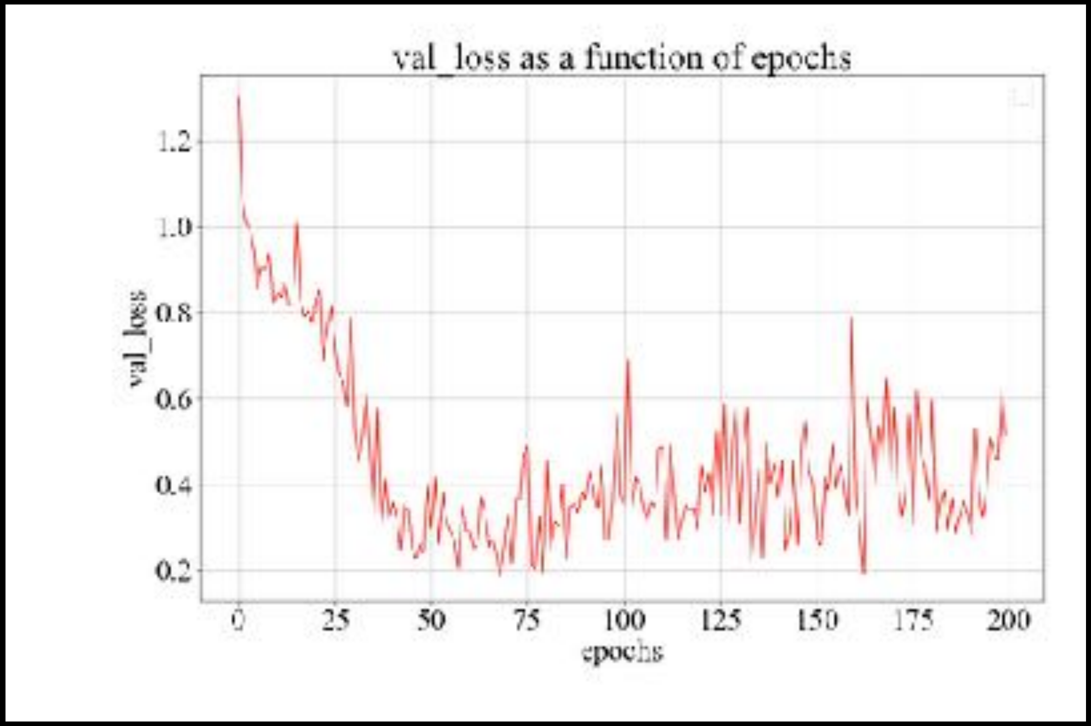
Size Ratio, z=0









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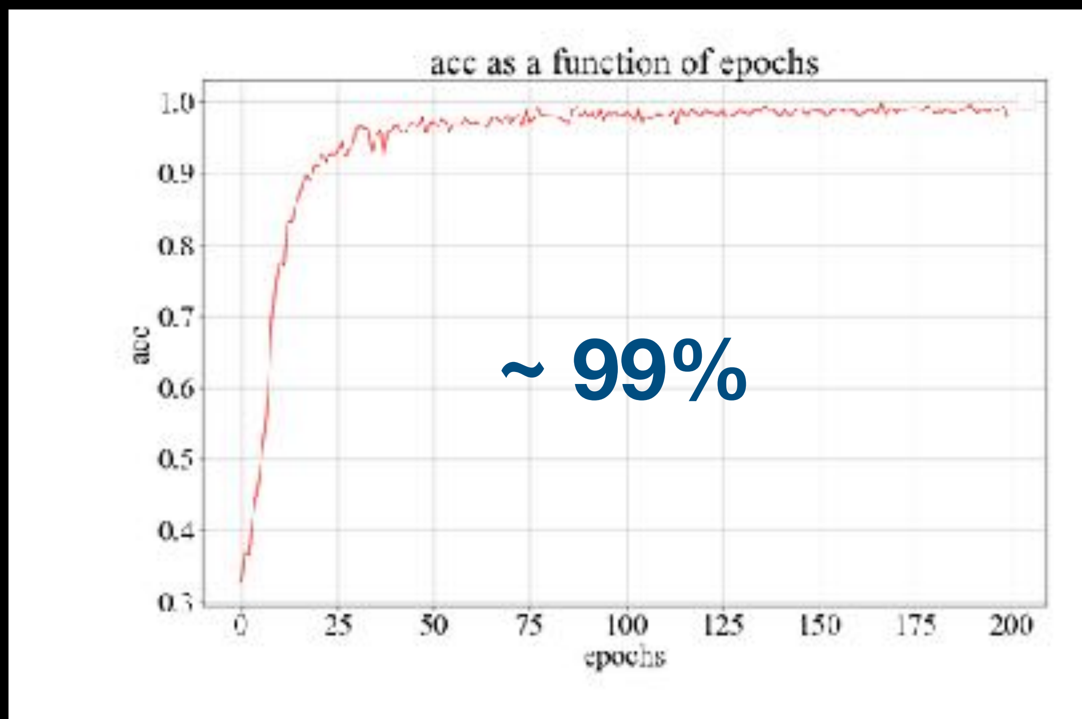
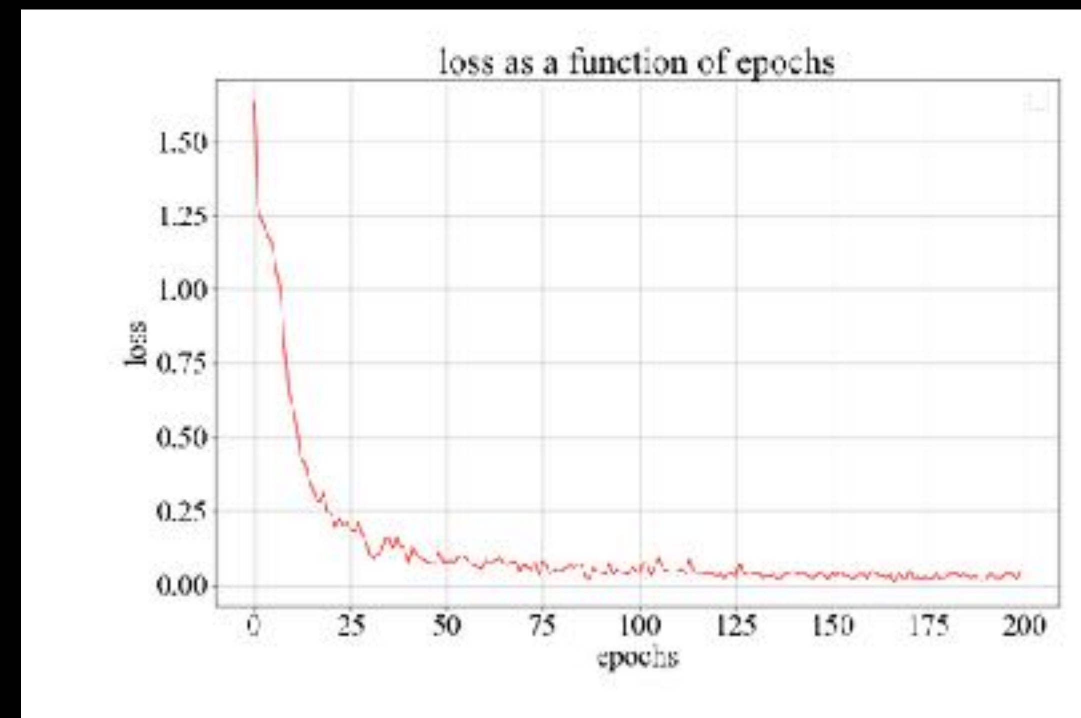
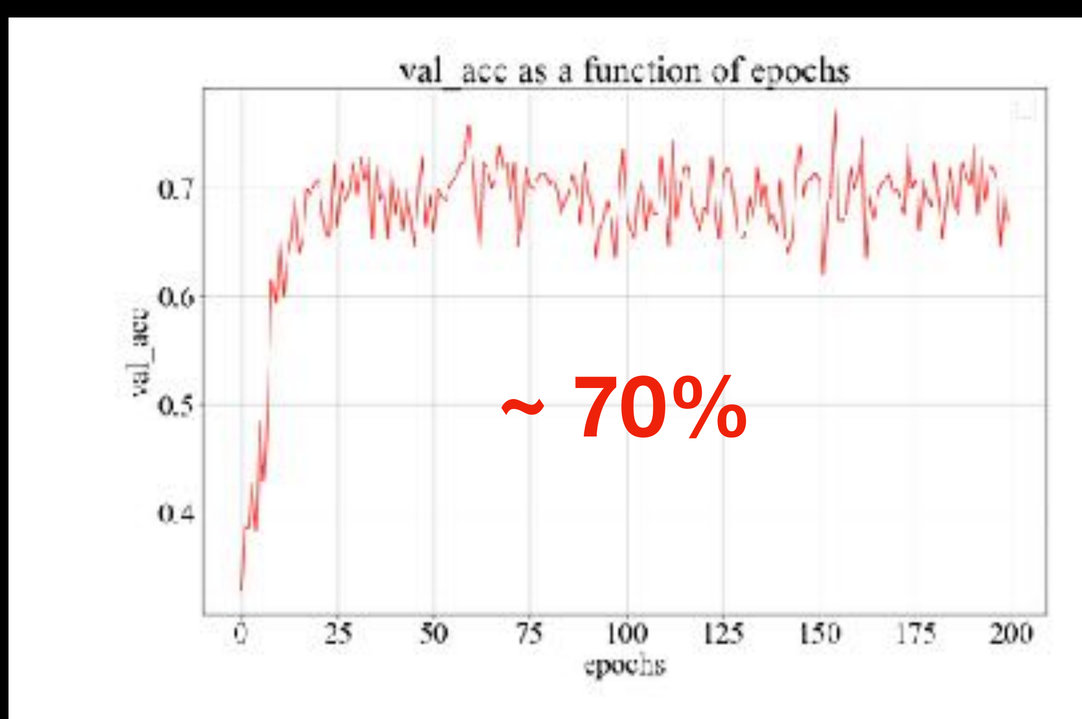
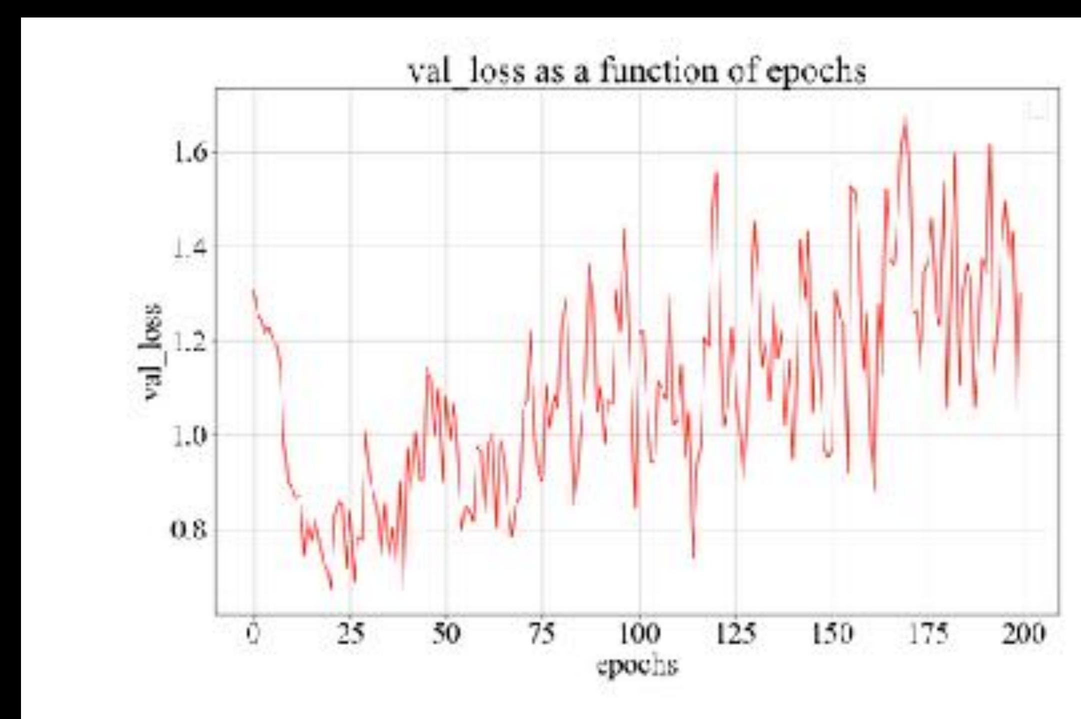
Size Ratio, z>0









Conclusion

1. Galaxy mergers are important to the understand galaxy evolution as they contribute to its mass growth and change in morphology.

2. It is hard to determine galaxy merger properties from observations.

3. Since we know everything about our simulation, we aim to infer observed galaxy merger properties with simulation data.

4. We have chosen EAGLE simulations to generate galaxy merger images.

5. We explore the properties that can be extracted from the images and choose visually apparent properties like mass and size ratio.

6. We train a DNN on the generated images of galaxy mergers against these properties.

7. The results show that:

    - For mass ratio z=0, valid accuracy achieved ~ 85%
    - For mass ratio z>0, valid accuracy achieved ~ 80%
    - For size ratio z=0, valid accuracy achieved ~ 90%
    - For size ratio z>0, valid accuracy achieved ~ 70%

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Future work

- A different zooming technique.
- More augmentation techniques.
- To generate images of a higher resolution by upsampling from EAGLE simulations.
- Predicting on more properties like relative velocity, collision angle.
- Transfer Learning for faster and higher accuracy training.

Take home message

- We can deduce properties of galaxy mergers using a trained NN from observations and quantitatively understand observations.

Parameters of the network

- Epochs : 200
- accuracy: categorical accuracy
- Loss: categorical crossentropy
- Optimizer: Stochastic Gradient Descent
- Learning rate: 0.01
- Decay: 1e-06
- Momentum: 0.95
- Classes: 4
- Training:
  - z=0: 628 images
  - z>0: 670 images
- Test:
  - z=0: 308 images
  - z>0: 330 images
- Batch size: 64